Dynamic Processes in Marketing – An Application of Multilevel Models to Assess Firm and Salesperson Performance Development

Dissertation
submitted to the Faculty of Economics,
Business Administration and Information Technology
of the University of Zurich

to obtain the degree of
Doktorin der Wirtschaftswissenschaften, Dr. oec.
(corresponds to Doctor of Philosophy, PhD)

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The Faculty of Economics, Business Administration and Information Technology of the University of Zurich hereby authorizes the printing of this dissertation, without indicating an opinion of the views expressed in the work.

Zurich, 11.02.2015

Chairman of the Doctoral Board: Prof. Dr. Josef Zweimüller

To my parents Renate and Friedrich,
and my little sister Friederike:

This dissertation would never have been
possible without your unrestricted support,
encouragement, patience, trust, and love.
Words cannot even begin to describe
how thankful I am to you.

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List of Abbreviations

ACSI	American Customer Satisfaction Index
AIC	Akaike information criterion
BIC	Bayesian information criterion
BU	Business unit
Chisq	Chisquare
df	Degrees of freedom
Est.	Estimate
FIML	Full information maximum likelihood
GDP	Gross domestic product
GEE	Generalized estimating equations
GLMM	Generalized linear mixed model
GLS	Generalized least squares
ICC	Inter-class correlation
LCGA	Latent class growth analysis
LMM	Linear mixed model
MSEM	Multilevel structural equation models
ref	Random effect
REML	Restricted maximum likelihood
SE	Standard error
Sig.	Significance (level)
STD	Standard deviation

1 Introduction

1.1 Dynamic processes in marketing

Today's market environment is characterized by continuous changes and dynamic processes. Although dynamic in nature, practitioners and researchers assess performance mostly as being a static snapshot or in terms of short-term changes. However, today's firm records provide an opportunity to accurately measure performance development mid- to long-term. Considering developmental trajectories is important not only to accurately evaluate current but also to improve the prediction of future performance. As such, monitoring performance and its drivers from a dynamic perspective should be a task of highest priority to any manager to ensure firm or salesperson success.

This **dissertation contributes to marketing research in two ways**: From a practical point of view, this dissertation provides new insights into the management of performance development of firms and salespersons by considering various dynamic performance drivers. From a methodological point of view, it highlights the importance of taking into account a hierarchical data structure by applying multilevel models which include time-varying effects.

This dissertation **consists of three papers which have been written as independent studies**. While the first study is of conceptual nature, study two and three are empirical research. However, the studies share a common goal: they highlight the practical and statistical usefulness of employing advanced modeling analytics. In particular, the focus is to deliver both generalizable results as well as additional insights on marketing dynamics for marketing research and practice.

Before giving a brief overview of each study, the next paragraphs provide an accessible, yet profound **introduction into multilevel models** and shows how a basic multilevel model can be applied to marketing questions. The terminology applied in this introduction is used throughout this dissertation.

1.2 Multilevel modeling as solution for hierarchically structured problems

Modeling the complexity of today's business world is widely regarded as key challenge for any empirical study in marketing. One of the most common questions is how to deal with the hierarchical structure inherent to most research problems. From a vast portfolio of products offered by multiple stores a consumer chooses those that meet his preferences. The consumer's decision depends further on a wide array of contextual factors such as the household he belongs to or the geographic region he lives in. Analogous, explaining the success of a multinational firm depends on understanding the impact of determinants on brand-, category-, and country-level. In chapter 3, country-level contextual effects are taken into account when analyzing the time firms need until reaching their first large increase in sales.

To disentangle the impact of the relevant contextual factors on all levels, an **appropriate methodological approach** is necessary. Multilevel models allow determining the relevance of each level, consider observed and unobserved heterogeneity, and relax the assumption of independence of observations (e.g., Hox 2010, Rabe-Hesketh and Skrondal 2006). Key to address these issues is to allow for residual components at each level in the hierarchy by partitioning the observed variance into within- and between cluster variance (Goldstein 2011). A detailed discussion on the rationale for applying multilevel models as well as a thorough literature review of exiting studies is provided in chapter 2.

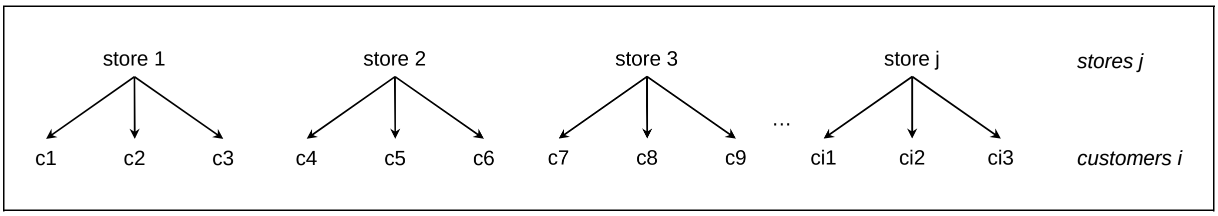
Multilevel analysis can also be applied in various other situations. Analyzing longitudinal data, where repeated observations are nested within individuals, is one field (e.g., Ahearne et al. 2010, Fu et al. 2010). Such data will be analyzed in the study presented in chapter 4. Other applications of multilevel models include the analysis of multivariate responses, repeat cross-sectional surveys, geographic variations, or interviewer-effects (for an overview see Diez-Roux 2000). Multilevel models are also used in meta-analyses (e.g., Krasnikov and Jayachandran 2008, Troy et al. 2008).

1.3 Statistical formulation of multilevel models

Basically, **two different types of multilevel models exist: random intercept and random slope models**. While the former account for heterogeneity in the overall response, the latter represent heterogeneity in the effects of covariates on the dependent variable (Skrondal and Rabe-Hesketh 2004). The following paragraphs review those two basic approaches by explaining the underlying data structure, the notation of the model, as well as differences between the models.

For the following examples, we **assume to model a continuous response variable on customers i visiting different stores j** for purchasing goods. This example refers to a multilevel, data structure, i.e., customers (the level-one unit) are nested within stores (the level-two unit). The dependent variable, Y_{ij}, is assumed to be the customer's expenditures modeled as a continuous variable. Such models are called linear mixed models (LMM).[1] For now, we assume that customers are only observed at one point in time, that one customer only buys at one store, and that several customers buy at the same store. This data structure is purely hierarchical.[2] For this example, the multilevel data structure is depicted in Figure 1.1. We further introduce two explanatory variables. On the customer level, X_{ij} measures the customer's health awareness (measured on a rating scale from one to seven, seven indicating strong health awareness). On the store level, Z_j indicates the product range of the store (measured as a continuous variable, i.e., number of products).

Figure 1.1: Example of multilevel data structure



[1] For a discussion on generalized linear mixed models, i.e., models with other response types such as continuous or count, see chapter 1.3.4.
[2] Examples of not purely hierarchical data are discussed in chapter 2.

1.3.1 The random-intercept model

Assuming that observations in a group or cluster are independent, the basic equation of an **intercept-only model** is as follows:

$$\begin{aligned} & Y_{ij} = \beta + \varepsilon_{ij} \\ & \text{whereby } \varepsilon_{ij} \sim N(0, \sigma_{\varepsilon}^2) \end{aligned} \tag{1.1}$$

Y_{ij} is the dependent variable expenditures of customer i in store j, β is the overall mean (or grand mean) across all customers (independent from the store), and ε_{ij} are the residuals or error terms that are independent over customer i and stores j. However, customers buying at the same store are more similar to each other than to customers purchasing goods at a different store and are thus not independent from each other.

Introducing individual- and group-level covariates X_{ij} (e.g., a customer's health awareness) and Z_j (e.g., a store's product range) respectively, the intercept-only model is extended to a **random-intercept model**.[3] Thus, a regression model is fit to the individual measurements of customers i while accounting for systematic unexplained variation among stores j. By introducing store-level explanatory variables, the variation of the regression coefficients β can be explained (Hox 2010).

The random-intercept model can be written as follows:

$$\begin{aligned} & Y_{ij} = \beta_{0j} + \beta_{1j} X_{ij} + \varepsilon_{ij} \\ & \beta_{0j} = \gamma_{00} + \gamma_{01} Z_j + u_{0j} \\ & \beta_{1j} = \gamma_{10} \end{aligned} \tag{1.2}$$

Rearranging terms gives:

$$\begin{aligned} & Y_{ij} = \gamma_{00} + \gamma_{01} Z_j + \gamma_{10} X_{ij} + u_{0j} + \varepsilon_{ij} \\ & \text{whereby } \varepsilon_{ij} \sim N(0, \sigma_{\varepsilon}^2) \text{ and } u_{0j} \sim N(0, {\tau_0}^2) \end{aligned} \tag{1.3}$$

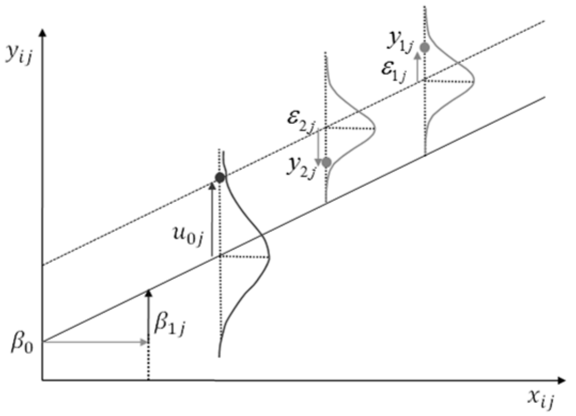
[3] It is to note, that the variance-components model is the simplest two-level model without explanatory variables. Splitting the total residual or error term ε_{ij} into two components u_{0j} and ε_{ij} accounts for the correlation and dependence of the data. The variance component model is also referred to as the one-way random-effects ANOVA model (Rabe-Hesketh and Skrondal 2008) or the empty or variance model (Snijders and Bosker 2012).

On the first level, a regression model is specified in which observations, i.e., customers (Y_{ij}, i=1,…, n_j), are nested within each of j level-two units, i.e., stores (j=1, …, J). β_{0j} and β_{1j} are level-one coefficients. On level two, β_{0j} is modeled as random intercept and β_{1j} as a fixed effect. Thereby, the level-one regression coefficients are given a probability model on the second level. $\beta_{0j} = \gamma_{00} + \gamma_{01} Z_j + u_{0j}$ predicts the average expenditure in a store (β_{0j}) by the store's product range (Z_j). For example, if γ_{01} is positive, the average customer expenditure is higher in stores with a wide product range. γ_{00}, γ_{01}, and γ_{10} represent fixed level-two coefficients which do not vary across stores (γ_{00} is the average level two intercept). u_{0j} is a random residual error term on store-level and is assumed to be independent from the residual error ε_{ij} on level one (Raudenbush and Bryk 2002). Parameters of the second-level model are also called the hyperparameters of the model estimated from the data (Gelman and Hill 2007).

A **graphical representation of the random-intercept model** with one individual-level covariate is shown in Figure 1.2, i.e., $Y_{ij} = (\gamma_{00} + u_{0j}) + \gamma_{10} X_{ij} + \varepsilon_{ij}$ (adopted from Rabe-Hesketh and Skrondal 2008).[4] The solid line represents $Y_{ij} = \gamma_{00} + \gamma_{10} X_{ij}$ which is – taken our example of customers i nested in stores j – the average regression line for all stores j. The dashed line shows the regression line for one specific store j. In this example, the store-specific regression line lies above the average regression line for all stores, indicating that the average customer expenditure is higher compared to the average. The random-intercept distribution is illustrated by the normal density curve centered on this line. u_{0j} indicates a (positive) random intercept for store j and produces the store-specific parallel dashed regression line $Y_{ij} = (\gamma_{00} + u_{0j}) + \gamma_{10} X_{ij}$. Observations of two customers $Y_{ij} = (\gamma_{00} + u_{0j}) + \gamma_{10} X_{ij} + \varepsilon_{ij},\ (i = 1, 2)$ are indicated. ε_{1j} and ε_{2j} are the within-store residual error terms.

[4] To simplify the graphical representation, no group-level variable Z_j is included.

Figure 1.2: Illustration of a random intercept model for one store j



Note: Adopted from Rabe-Hesketh and Skrondal (2008).

The explained **random-intercept model is the simplest two-level model** including explanatory variables. Only intercepts are assumed to be random implying that groups (i.e., customers buying at the same store) differ with respect to the average value of the dependent variable Y_{ij}. However, slopes may also be random. For example, the effect of a consumer's health awareness on his expenditures could differ between stores.

1.3.2 The random-slope model

By introducing a random slope to the equation, the model can be extended to a **random slope model** (also called random coefficient model) as follows.

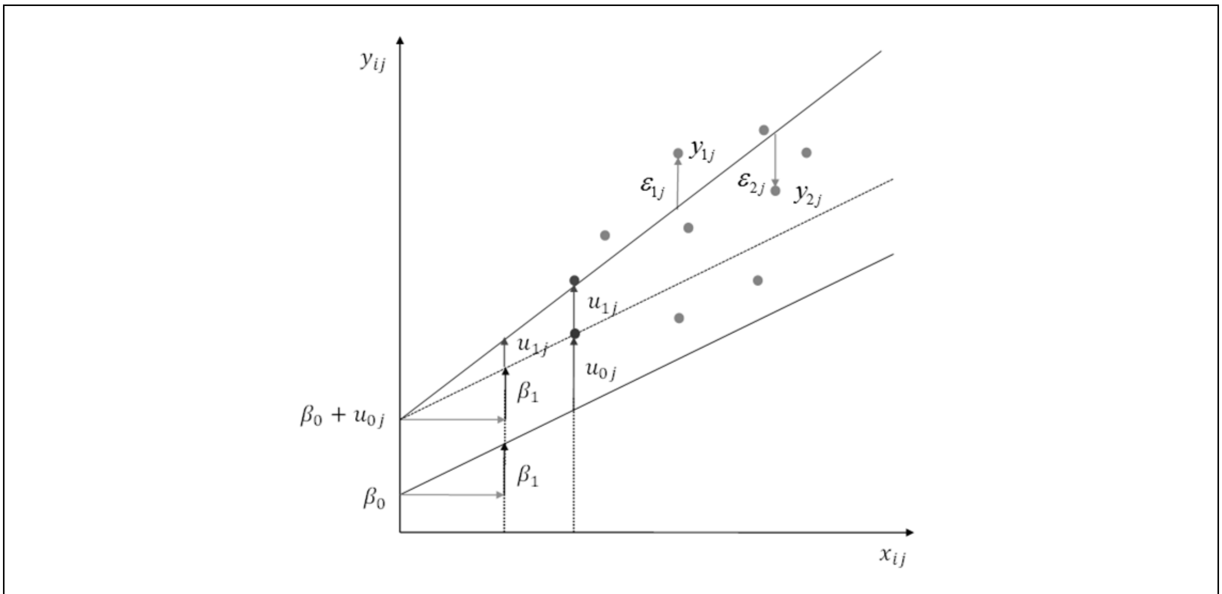
$$\begin{aligned} Y_{ij} &= \beta_{0j} + \beta_{1j} X_{ij} + \varepsilon_{ij} \\ \beta_{0j} &= \gamma_{00} + \gamma_{01} Z_j + u_{0j} \\ \beta_{1j} &= \gamma_{10} + \gamma_{11} Z_j + u_{1j} \end{aligned} \tag{1.4}$$

Rearranging terms gives:

$$\begin{aligned} & Y_{ij} = \underbrace{\left[\gamma_{00} + \gamma_{01} Z_j + \gamma_{10} X_{ij} + \gamma_{11} X_{ij} Z_j\right]}_{\text{fixed part}} + \underbrace{\left[u_{0j} + u_{1j} X_{ij} + \varepsilon_{ij}\right]}_{\text{random part}} \\ & \text{whereby} \\ & \varepsilon_{ij} \sim N(0, \sigma_\varepsilon^2) \text{ and} \\ & u_j \sim \begin{bmatrix} u_{0j} \\ u_{1j} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \tau_{00}^2 & \\ \tau_{10} & \tau_{11}^2 \end{bmatrix} \right) \end{aligned} \tag{1.5}$$

In addition to the effects described above, β_{1j} now represents the random slope coefficient. $\beta_{1j} = \gamma_{10} + \gamma_{11} Z_j + u_{1j}$ states that the relationship between expenditures Y_{ij} and the customer's health awareness X_{ij} depends on the product breadth of store j. For example, if γ_{11} is positive, the effect of health awareness on expenditure is larger in stores with a wide range of products. Both u-terms indicate the random residual error terms on store level. In equation 1.5, the term $X_{ij}Z_j$ indicates a cross-level interaction resulting from the estimation of the varying regression slope β_{1j} of the customer-level variable X_{ij} with the store-level variable Z_j (Hox 2010). The interpretation of interaction terms is very complex. Examples can be found in the studies in chapter three and four.

Figure 1.3: Illustration of a random coefficient model for one store j



Note: Adopted from Rabe-Hesketh and Skrondal (2008).

A **random-coefficient model with one covariate X_{ij} for a store j is illustrated** in Figure 1.3 (adopted from Rabe-Hesketh and Skrondal 2008). As has been indicated above, the lower solid line indicates the average regression line for all stores j, which is $Y_{ij} = \gamma_{00} + \gamma_{10} X_{ij}$.

The dashed line indicates the store-specific regression line in the random intercept model parallel to the average regression line for all stores deviating by u_{0j}. Contrary, the upper solid line is the store-specific regression line in a random slope model which can be expressed by $Y_{ij} = (\gamma_{00} + u_{0j}) + (\gamma_{10} + u_{1j})X_{ij} + \varepsilon_{ij}$ which, in this example, has a greater random slope (u_{1j}). The slope of the store-specific regression line depends on the effect of the customer-level explanatory variable (i.e., health awareness) which varies across stores. The vertical deviation between the store-specific regression line and the line for all stores j is $u_{1j}X_{ij}$. ε_{ij} are the within-store residual error terms.

It is to note, that sometimes data has **more than two levels.** We now consider the case of the following three-level hierarchy: customers i nested in stores j nested in countries k. The model is specified according to the two-level model, but slopes of level-one covariates can be specified as random effects at level two and level three. Following the same principles, this can be extended to higher-level hierarchies.

$$
\begin{aligned}
Y_{ijk} &= \beta_{0jk} + \beta_{1jk}X_{ijk} + \varepsilon_{ijk} \\
\beta_{0jk} &= \gamma_{00k} + \gamma_{01k}Z_{jk} + u_{0jk} \\
\beta_{1jk} &= \gamma_{10k} + \gamma_{11k}Z_{jk} + u_{1jk} \\
\gamma_{00k} &= \delta_{000} + \delta_{001}Q_{1k} + v_{00k} \\
\gamma_{01k} &= \delta_{010} + \delta_{011}Q_{1k} + v_{01k} \\
\gamma_{10k} &= \delta_{100} + \delta_{101}Q_{1k} + v_{10k} \\
\gamma_{11k} &= \delta_{110} + \delta_{111}Q_{1k} + v_{11k}
\end{aligned}
$$

$$
\begin{aligned}
&\text{whereby} \qquad (1.6)\\
&\varepsilon_{ijk} \sim N(0, \sigma_\varepsilon^2) \\
&u_{jk} \sim \begin{bmatrix} u_{0jk} \\ u_{1jk} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \tau_{00}^2 & \\ \tau_{10} & \tau_{11}^2 \end{bmatrix} \right) \\
&v_k \sim \begin{bmatrix} v_{00k} \\ v_{01k} \\ v_{10k} \\ v_{11k} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \psi_{000}^2 & & & \\ \psi_{100} & \psi_{111}^2 & & \\ \psi_{200} & \psi_{211} & \psi_{222}^2 & \\ \psi_{300} & \psi_{311} & \psi_{322} & \psi_{333}^2 \end{bmatrix} \right)
\end{aligned}
$$

For the previous examples, it has been assumed that customers buy at a store at only one point in time. However, **customers can also be observed over a longer time period**. Models for data that has repeated measures for individuals over time are similar to the ones discussed above and are explained in the following.

1.3.3 Multilevel models for repeated measures

Multilevel models can also be applied to **longitudinal data**. In fact, longitudinal data can be seen as a special case of multilevel data as they are necessarily multilevel (Samaha et al. 2011). In a marketing context, e.g., purchase occasions over several years for different customers can be observed, thus purchase occasions are nested within customers. The individual becomes the higher level unit while time is specified as level-one unit.

Scientific questions related to repeated measures data deal with either stability or change (Rovine and Walls 2006). Stability refers to the extent to which a future occasion can be predicted from the current occasion, while change refers to the extent to which patterns can be identified across all occasions. Respectively, we distinguish between (1) lagged regression panel models and (2) growth curve models.

An example for a lagged regression panel model is the **autoregressive model** which is used to describe serial dependencies (Box et al. 2008). Such models are usually applied to describe the within-subject variation in contexts where repeated measures are obtained from one subject (Rovine and Walls 2006, p. 130). In such a model, the autoregressive relationships are modeled through the coefficients $\beta_{t,t-k}$ indicating two measurement occasions separated by lag k (Rovine and Walls 2006). Taking the example of a multilevel AR(1) model, the model can be specified as follows:

$$
\begin{aligned}
&Y_{ti} = \beta_{0i} + \beta_{t,t-1,i} y_{t-1,i} + \varepsilon_{ti} \\
&\beta_{t,t-1,i} = \gamma_0 + \gamma_1 x_1 + \gamma_2 x_2 + u_{t,t-1,i} \\
&\text{whereby} \\
&\varepsilon_{ti} \sim N(0, \sigma_\varepsilon^2) \\
&u_{t,t-1,i} \sim N(0, \sigma_u^2)
\end{aligned}
\tag{1.7}
$$

To model existence, nature, and causes of individual change over time, a **growth curve model** can be specified (Deadrick et al. 1997). To model the individual trajectories of change, equation 1.4 is extended by an effect of time (TIME_{ti}), which is added on the first level indicating the purchase occasion t of customer i.

$$\begin{aligned} Y_{ti} &= \pi_{0i} + \pi_{1i}\text{time}_{ti} + \pi_{2i}X_{ti} + \varepsilon_{ti} \\ \pi_{0i} &= \beta_{00} + \beta_{01}Z_i + u_{0i} \\ \pi_{1i} &= \beta_{10} + \beta_{11}Z_i + u_{1i} \\ \pi_{2i} &= \beta_{20} + \beta_{21}Z_i + u_{2i} \end{aligned} \tag{1.8}$$

π is now used to express level-one coefficients. Thus, β, as has been done in the previous models, still refers to the individual customer-level coefficients which are now the level-two unit. Rearranging terms yields the following formula:

$$\begin{aligned} Y_{ti} = {} & \beta_{00} + \beta_{10}\text{time}_{ti} + \beta_{20}X_{ti} + \beta_{01}Z_i + \beta_{11}Z_i\text{time}_{ti} + \beta_{21}Z_iX_{ti} + u_{1i}\text{time}_{ti} \\ & + u_{2i}X_{ti} + u_{0i} + \varepsilon_{ti} \end{aligned}$$

$$\begin{aligned} &\text{whereby} \\ &\varepsilon_{ti} \sim N(0, \sigma_\varepsilon^2) \\ &u_j \sim \begin{bmatrix} u_{0j} \\ u_{1j} \\ u_{2j} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \tau_{00}^2 & & \\ \tau_{10} & \tau_{11}^2 & \\ \tau_{20} & \tau_{21} & \tau_{22}^2 \end{bmatrix} \right) \end{aligned} \tag{1.9}$$

X_{ti} indicates a time-varying covariate, while Z_i is a time-invariant variable on level two. Besides a linear specification, time can also be modeled as a nonlinear effect. For example, quadratic or cubic terms can be included by simply adding TIME_{ti}^2 and TIME_{ti}^3.

1.3.4 Generalized linear mixed models

In the models presented above, only the case of a continuous dependent variable has been considered and, thus, the case of a linear mixed model (LMM) has been explained. **Generalized linear mixed models (GLMM) extend LMMs to allow other response types**, e.g., dichotomous or counts. GLMM are an extension of GLM which are generalizations of linear models (for an overview of the historic development of GLM and GLMM see Gbur et al.

(2012)). GLM can be characterized by three components: (1) a systematic part, (2) a link function, and (3) the specification for the form of the variance (Nelder and Wedderbrun 1972). The latter two depend on the distribution of the response variable, which is assumed to be any member of the natural exponential dispersion family (Hedeker 2005). The three components will be explained in more detail in the following.

1. The **systematic component of a GLM** is a linear function of predictor variables:

   $$\eta_i = x_i'\beta \tag{1.10}$$

   where β is a vector of regression coefficients and x_i' is a vector of values on the predictor variables for consumers i. Termed "linear predictor", this fixed structural part of the model explains the systematic variability between means.

2. The **link function** converts the expected value μ_i of the outcome variable y_i (i.e., $\mu_i = E[y_i]$) to the linear predictor η_i:

   $$g(\mu_i) = \eta_i \tag{1.11}$$

   The expected value in turn equals the inverse transformation of $g()$:

   $$\mu_i = g^{-1}(\eta_i) \tag{1.12}$$

3. Finally, a **specification for the form of the variance** in terms of the mean μ_i is made:

   $$V(\mu_i) = V(g^{-1}(x_i'\beta)) = V(g^{-1}(\eta_i)) \tag{1.13}$$

Extending a GLM to a GLMM, random effects γ_i are added to the linear predictor η_{ij}:

$$\eta_{ij} = x_{ij}'\beta + z_{ij}'\gamma_i \tag{1.14}$$

whereby x_{ij} is the (n×p) design matrix of rank k for (p×1) fixed effects β and z_{ij} is the (n×q) design matrix for (q×1) random effects γ_i. It follows that the expected value of the response variable μ_{ij}, which is related to the linear predictor η_{ij} via the link function $g()$[5], has to be expressed as the conditional distribution of the response variable given the random effects

$$\mu_{ij} \sim \mathrm{E}[y_{ij} | \gamma_i] \tag{1.15}$$

whereby y_{ij} represents a (n×1) vector of responses for e.g., customers I in stores j. Summarizing, the expectations of the GLMM are:

$$\mathrm{E}[y_{ij} | \gamma_i] = g^{-1}(x'_{ij}\beta + z'_{ij}\gamma_i). \tag{1.16}$$

While in the linear mixed models the **residual variability** is usually modeled by adding a vector of residuals ε_{ij}, the relationship between the linear predictor η_{ij} and the vector of observations y_{ij} in a GLMM is modeled by an alternative approach. This is:

$$y_{ij} | \gamma_i \sim (g^{-1}(\eta_{ij}), \mathbf{R}). \tag{1.17}$$

In other words, the conditional distribution of the response vector y_{ij} given the random effects γ_i has mean $g^{-1}(\eta_{ij})$ and variance R.

A further assumption is that the **vector of random effects** $\boldsymbol{\gamma}_i$ follows a multivariate normal distribution with mean vector 0 and variance-covariance matrix G:

$$\boldsymbol{\gamma}_i \sim \mathrm{N}(0, \mathbf{G}). \tag{1.18}$$

The **previous paragraphs provide an introduction to multilevel models**. It has been highlighted that two types of models exist, LMM and GLMM. Whether LMM or GLMM, random intercept and random slope models can be applied. While the former account for heterogeneity in the overall response, the latter represent heterogeneity in the effects of covariates on the dependent variable (Skrondal and Rabe-Hesketh 2004). Despite its importance and

[5] For example, in case of a mixed-effects linear regression model $g(\mu_{ij}) = \eta_{ij}$ or in case of a mixed-effects logistic regression model $g(\mu_{ij}) = \mathrm{logit}(\mu_{ij}) = \log\left[\dfrac{\mu_{ij}}{1-\mu_{ij}}\right] = \eta_{ij}$.

flexibility to model complex data, applications have predominantly been used in disciplines such as psychology, sociology, medicine, or education. Compared to other modeling approaches, the discussion and application of multilevel models in marketing is rather limited.[6]

1.4 Overview of studies in this dissertation

This **dissertation contributes to existing research in several ways**: In the first study, for the first time, a structured overview of existing studies applying a multilevel modeling approach in the top-tier marketing research journals is provided. In the second study, the concept of firm-level takeoff is introduced for the first time. The setup of this study does not only allow to disentangle the relationship between category- and firm-level takeoff but to consider contextual effects on country-level. The third study is the most comprehensive longitudinal study on salespersons' performance. Acknowledging the long neglected dynamic nature of performance, the dynamic impact of time-varying determinants on salespersons' performance is the focus of this study. Table 1.1 gives an overview of all studies in this dissertation by highlighting each study's underlying research questions, core contributions and data basis.

[6] It is to note that several estimation procedures can be used to estimate the statistical parameters of multilevel models. It is not in the scope of this introduction to outline the estimation procedures in great detail. The following references give an overview of the procedures, the different algorithms used to carry out the procedures, and their application to multilevel models: For a detailed explanation of maximum likelihood estimation (either full information maximum likelihood (FIML) or restricted maximum likelihood (REML)), applications of Bayesian techniques to multilevel models, as well as an overview of additional estimation procedures such as generalized least squares (GLS), generalized estimating equations (GEE), marginal quasi likelihood, penalized quasi likelihood, and bootsrapping, I recommend Allenby et al. (2005), Gelman et al. (2004), Gelman and Hill (2007), Goldstein and Rasbash (1996), Hox (2010), Raudenbush and Bryk (2002), Rodríguez and Goldman (2001), Rossi and Allenby (2003), Snijders and Bosker (2012), and Van Birgelen et al. (2002).

Table 1.1: Overview of the thesis structure

Research questions	Core contributions	Data basis
***Study 1:** Take it to the next level - Applications and extensions of multilevel models in Marketing (conceptual study)*		
(1) Why should multilevel models be applied to marketing questions? (2) In which areas within marketing is multilevel modeling part of the researcher's standard toolbox and in which areas do multilevel models provide a fruitful avenue for future research? (3) Which avenues for future research in marketing are provided through recent extensions of multilevel modeling?	- Providing a structured overview of reasons on why to apply multilevel models to marketing questions - Providing a structured overview of existing studies applying multilevel models in top-tier marketing journals - Providing a discussion of recent advances in multilevel modeling and their importance for future marketing research	Articles published between 1990 and 2013 in the Journal of Marketing, Marketing Science, the Journal of Marketing Research, the International Journal of Research in Marketing, and the Journal of the Academy of Marketing Science applying a multilevel modeling approach.
Main results - Identification of substantive and statistical reasons for applying multilevel models - Identification of the following five marketing research areas in which multilevel models have been applied: (1) new product success, (2) consumer preferences, (3) customer retention, (4) marketing strategy, and (5) internal marketing. - Three major issues mark the existing studies: (1) terminology and documentation varies widely, (2) several extensions of multilevel modeling will affect the future use of such techniques in marketing, (3) multilevel theories are rather scarce.		
***Study 2:** A close look at the international takeoff of new products – The relationship between category- and firm-level takeoff (empirical study)*		
Research questions	**Core contributions**	**Data basis**
(1) Does firm-level takeoff depend on category-level takeoff? (2) Does competition influence firm-level takeoff? (3) Does the economic status of a country influence firm-level takeoff?	- Applying the concept of takeoff to firm-level data - Emphasizing the effect of country-specific category-level takeoff as an indicator of individual firms' success - Introducing the timing of market entry in relation to category-level takeoff as a new metric to predict new product success - Applying a random coefficient discrete-time hazard model to account for observed and unobserved heterogeneity at the country level	Quarterly subscriber rates of 428 (74.9% of all broadband Internet operators worldwide) broadband Internet operators across 81 countries from 1996 to 2011 covering the product lifecycle of broadband Internet services from its launch until today
Main results - Firm-level takeoff depends on a firm's decision to enter a market before or after category-level takeoff. - The impact of this decision is moderated by the time difference between a firm's market entry and category-level takeoff. - Fewer competitors increase the likelihood of reaching firm-level takeoff in countries with a lower economic status, whereas this effect is negligible in other countries.		

Table 1.1 (continued)

Study 3: *The dynamic effects of relational and transactional selling strategies on salesperson performance (empirical study)*		
Research questions	**Core contributions**	**Data basis**
(1) How does a salespersons' relational selling strategy influence salesperson performance? (2) How does a salespersons' transactional selling strategy influence salesperson performance? (3) What are the dynamics of both relationships?	- Disentangling the dynamic effects of transactional and relational selling strategies on salesperson performance - Using the most comprehensive longitudinal dataset on salesperson performance to date - Presenting a random coefficient (growth curve) model that allows practitioners to contrast individual performance with the average	Monthly sales figures of 812 independent salespersons from the tourism industry from April 2005 to September 2013, covering the whole time span since the firm started its operation
Main results		
- (1) The functional form of the relationship between relational selling strategy and salesperson performance has an inverted U-shape. The impact of this relationship changes over time, i.e., the impact of relational selling strategy increases with a salesperson's tenure. - With regards to a salesperson's transactional selling strategy, we find that (2) price specialization enhances salesperson performance, but its importance decreases with time. Further, (3) product specialization and (4) selling more in advance both increase salesperson performance whereby the importance of both effects increases with time. (5) Geographic proximity enhances salesperson performance regardless of time.		

1.4.1 Summary of study one (chapter 2)

In the first study, we analyze the state of the art of multilevel modeling in marketing research. To provide meaningful insights, analytics have to be able to adequately address the complexity of today's business world. Marketing phenomena and related data often have a hierarchical structure. For instance, customers are part of a household, they buy products at different stores, or live in different countries. When analyzing such data, researchers have to take into account the variability on all levels, i.e., between customers as well as between households. Ignoring those different sources of variability may lead to biased model results, incorrect interpretation and false conclusions.

Across disciplines, multilevel research in general as well as multilevel models in particular received much attention. However, **despite its importance to marketing, a broad discussion is missing**. One of the most common questions is how to deal with the hierarchical structure inherent to most research problems, whether the focus is on the consumer or the firm. Multilevel models allow to rigorously disentangle the impact of relevant factors on individual- and group-level as they (a) relax the assumption of independence of observations, (b) address the issue of observed and unobserved heterogeneity, (c) increase the predictive accuracy as well as (d) facilitate the generalization of findings beyond the groups in the sample.

The study has three goals. First, by providing an accessible, yet profound introduction into multilevel models, their usage among applied marketing researcher and marketers should be promoted. Second, reviewing the marketing literature since 1990 in detail, five areas are identified in which multilevel models have been applied in the past. Those areas are: (1) new product success, (2) consumer preferences, (3) customer retention, (4) marketing strategy, and (5) internal marketing. This overview provides not only a practical guidance when to apply multilevel models, but also shows avenues for further research within each area. Third, we discuss issues raised concerning the terminology used for and documentation of multilevel models and highlight and explain extensions of multilevel models which have been rarely applied in marketing.

1.4.2 Summary of study two (chapter 3)

In the second study, we examine determinants of firm success by analyzing the relationship between firm- and category-level takeoff across countries. Takeoff is a critical success factor for new products and services. It is defined as the point where the first large increase in sales occurs. Product managers want to know whether and when to enter a market with their product, whether to further invest in their product in an existing market, and whether and when to take a product off the market depending on recent market conditions. Product takeoff has been introduced as an instrument to support the decision making of product managers in these situations.

It is essential for firms to predict the success of new products early. Thus far, studies have only analyzed the takeoff of new product categories. However, practitioners not only need to know when aggregated product sales in a specific category take off. They need to be able to predict the takeoff of their firms' products. This paper introduces the concept of firm-level takeoff as a more precise measure for predicting and benchmarking the success of new products across various country markets. Besides indicating customers' acceptance of a product or service, knowing the timing of takeoff helps to guide resource allocation and to decide whether to enter or leave a market.

An **analysis of 428 broadband Internet operators in 81 countries** reveals the relationship between firm-level and category-level takeoff. The impact of the competitive setting on firm-level takeoff across countries with different economic statuses is also analyzed. A random coefficient discrete-time hazard model is applied, and the results indicate the following findings: (1) Firm-level takeoff depends on a firm's decision to enter a market before or after category-level takeoff. (2) The impact of this decision is moderated by the time difference between a firm's market entry and category-level takeoff. (3) Fewer competitors increase the likelihood of reaching firm-level takeoff in countries with a lower economic status, whereas this effect is negligible in other countries. Theoretical as well as managerial implications are discussed in detail.

1.4.3 Summary of study three (chapter 4)

In the third study, we analyze the dynamic effects of relational and transactional selling strategy on salesperson performance. Most firms rely heavily on the success of its salespersons. They build the direct link between a firm and its prospective and existing customers. Sales managers regularly evaluate the salesperson's performance to optimize their short and long-term success, e.g., by identifying salespersons who need coaching in either building customer relationships or increasing selling efficiency. A decision support system has to build up on a model which takes into account the dynamic nature of performance as well as the dynamic impact of individual and contextual effects.

Analyzing the drivers of salesperson performance has gained significant attention in the marketing literature. However, studies so far have widely neglected the dynamic effects of building long-term salesperson-customer relationships as well as of transactional elements on salesperson performance. Filling those gaps, our research takes a closer look at the influence of those effects on sales performance and analyzes in specific how the dynamics of those relationships look like.

We use a unique **dataset covering monthly sales records from 2005 till 2013 of 812 salespersons** of a leading European service firm. Applying growth curve modeling to analyze the performance trajectories of individual salespersons, the study reports the following results: (1) the functional form of the relationship between relational selling strategy and salesperson performance has an inverted U-shape; the impact of this relationship increases with a salesperson's tenure; With regards to a salesperson's transactional selling strategy, we find that (2) price specialization enhances salesperson performance, but its importance decreases with time. Further, (3) product specialization and (4) selling more in advance both increase salesperson performance whereby the importance of both effects increases with time. Regardless of time, (5) geographic proximity enhances salesperson performance. We address the implications of these results in great detail and illustrate how sales manager can assess individual performance.

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2 Take it to the Next Level - Applications and Extensions of Multilevel Models in Marketing Research

Abstract

Modeling the complexity of today's business world is widely regarded as key challenge for any empirical study in marketing. One of the most common questions is how to deal with the hierarchical structure inherent to most research problems, whether the focus is on the consumer or the firm. Multilevel models allow to rigorously disentangle the impact of relevant factors on individual- and group-level. This paper has three goals. First, by providing an accessible, yet profound overview of reasons for applying multilevel models, their usage among applied marketing researcher and marketers should be promoted. Second, reviewing the marketing literature since 1990 in detail, five marketing research areas are identified in which multilevel models have been applied in the past. Those areas are: (1) new product success, (2) consumer preferences, (3) customer retention, (4) marketing strategy, and (5) internal marketing. This overview provides not only practical guidance when to apply multilevel models, but also shows avenues for further research within each area. Third, we discuss issues raised concerning the terminology used for and documentation of multilevel models and highlight extensions of multilevel models which have been rarely applied in marketing and explain how they can be used to answers substantive questions which have not been researched before.

Keywords: *Multilevel models, marketing research, literature review*

Publication note: This article is a working paper and has not yet been submitted to any journal. It is a single-author paper.

2.1 Introduction

Modeling the complexity of today's business world is widely regarded as key challenge for any empirical study in marketing. One of the most common questions is how to deal with the hierarchical structure inherent to most research problems, whether the focus is on consumers or firms. From a vast portfolio of products offered by multiple stores a consumer chooses those that meet his preferences. The consumer's decision depends further on a wide array of contextual factors such as the household he belongs to or the geographic region he lives in. Analogous, explaining the success of a multinational firm depends on understanding the impact of determinants on brand-, category-, and country-level. Those settings are both ubiquitous in marketing research and essentially hierarchically structured.

To disentangle the impact of the relevant contextual factors on all levels, an **appropriate methodological approach** is necessary. Multilevel models allow determining the relevance of each level, consider observed and unobserved heterogeneity, and relax the assumption of independence of observations (e.g., Hox 2010, Rabe-Hesketh and Skrondal 2006). Key to address these issues is to allow for residual components at each level in the hierarchy by partitioning the observed variance into within- and between cluster variance (Goldstein 2011).

Multilevel analysis can also be applied in various other situations. Analyzing longitudinal data, where repeated observations are nested within individuals, is one field (e.g., Ahearne et al. 2010, Fu et al. 2010). Other applications of multilevel models include the analysis of multivariate responses, repeat cross-sectional surveys, geographic variations, or interviewer-effects (for an overview see Diez-Roux 2000). Multilevel models are also used in meta-analyses (e.g., Krasnikov and Jayachandran 2008, Troy et al. 2008).

Despite its general applicability, **multilevel models have gained mixed attention across various areas in marketing**. Even though multilevel models are increasingly applied in various disciplines, many marketers and marketing researchers still hesitate to apply those models. Across disciplines, multilevel research in general as well as multilevel models in particular received much attention. Despite its importance to marketing, a broad discussion is missing. Comparable papers have been published in top-tier outlets in various disciplines and are highly cited, for example, management (Aguinis et al. 2013, Hitt et al. 2007, Hofmann 1997, Ozkaya et al. 2013), educational research (Dedrick et al. 2009, Schreiber and Griffin 2004), psychology (Hoffman and Rovine 2007, Nezlek 2001), health research (Diez-Roux 2000, Duncan et al. 1998), sociology (DiPrete and Forristal 1994), political science (Steenbergen and Jones 2002), medicine (Greenland 2002, Moerbeek et al. 2003), genetics (Guo and Wang 2002), as well as ecology (Bolker et al. 2008). However, the past efforts in marketing have been rather limited (Wieseke et al. 2008b). Kim et al. (1995) give an initial overview on early studies in marketing which implement the multilevel approach in choice modeling to account for observed and unobserved heterogeneity. Baltas and Doyle (2001) give more details on the use of random-effects models in this domain. Further, established and more recent extensions of multilevel models, such as cross-classified multi-membership models, multilevel mixture models, and multilevel structural equation models have only rarely been applied in marketing literature.

Summing up, this paper **answers the following questions**:

(1) Why should multilevel models be applied to marketing questions?

(2) In which fields within marketing is multilevel modeling part of the researcher's standard toolbox and in which fields does multilevel modeling provide a fruitful avenue for future research?

(3) Which avenues for future research in marketing are provided through recent extensions of multilevel modeling?

By answering these questions, we **provide a comprehensive overview on the current use of multilevel models in marketing and avenues for future research**. In particular, reviewing papers published between 1990 and 2013 in the Journal of Marketing, Marketing Science, the Journal of Marketing Research, the International Journal of Research in Marketing, and the Journal of the Academy of Marketing Science provides detailed insights when to apply those models and thus bridges the gap between statistical theory and application. We identify five marketing research areas in which multilevel models have been applied: (1) new product success, (2) consumer preferences, (3) customer retention, (4) marketing strategy, and (5) internal marketing.

Our study differs from previous work in several ways. First, we provide an accessible, yet rigorous overview of reasons for applying multilevel models. Second, this is the first study to summarize and group the existing studies applying multilevel models in marketing. Third, we provide a discussion of recent advances in multilevel modeling and their importance for future marketing research.

The **remainder of this paper** is organized as follows. In the second section, we highlight substantive and statistical reasons for applying multilevel models. In the third section, we outline the procedure of our literature review. In the fourth section, the results of the literature review on multilevel models in marketing are discussed. In the fifth section, we highlight challenges in multilevel modeling and provide an overview of recent advances becoming important for future marketing studies.

2.2 Rationale for multilevel model applications

Both, substantive and statistical reasoning highlight the importance of multilevel models. From a substantive perspective, multilevel models allow (1) a correct inference for predictor variables on any levels, (2) determining the importance of each level to explain the research question, and (3) generalizing the findings beyond the groups in the sample. From a statistical perspective, multilevel models have some statistical properties that allow researchers to make the right inferences, i.e., they (1) relax the assumption of independence of observations, (2) address the issue of observed and unobserved heterogeneity, (3) increase the predictive accuracy, and (4) are robust in case of unbalanced designs. Multilevel models have been proven to be superior in accounting for those issues compared to traditional approaches such as including fixed effects for each group-level unit (Steenbergen and Jones 2002). Those reasons are discussed in detail in the following.

From a substantive perspective, **predictor variables may be included for both levels** simultaneously describing individual- as well as group-level units to account for observed heterogeneity (Aguinis et al. 2013, Wieseke et al. 2008b). Using variables on different levels improves the power of the model and, thus, for example, allows marketers to better understand customer preferences and their target market and to better decide on segmentation strategies (Steenburgh et al. 2003). Further, modeling cross-level interactions is possible and enables researcher to draw conclusions on whether the impact of individual-level variables, such as consumer preferences, depends on certain group-level variables such as product and/or store characteristics (e.g., Ahearne et al. 2013b, Hughes and Ahearne 2010, Schmitz 2013, Van Birgelen et al. 2002, Wieseke et al. 2008a).[1]

Further, multilevel models allow **determining the importance of each level to explain the research question at hand**. Using multilevel models, the degree of shared variance between individual-level units belonging to the same group can be calculated. This information can not only be used to answer substantive hypotheses, but as an initial test whether a multilevel model is justified in addition to comparing fixed-effect and random-effect models by likelihood ratio (or deviance) tests and by looking at the design effect (Snijders and Bosker 2012). Besides, examining the inter-individual and inter-group variation, the contributions of individual-level and group-level variables to these variations can be determined.

[1] See Aguinis et al. (2013) for a detailed explanation on how to incorporate cross-level interactions in multilevel models.

Another advantage from a substantive point of view is the **generalizability of the findings beyond the groups in the sample** (e.g., DiPrete and Forristal 1994, Steenbergen and Jones 2002). Contrary to the analysis based on a fixed-effects regression model which is only valid for the group units surveyed, the multilevel model assumes the groups to be drawn from a distribution and as such the findings apply to the entire population of groups, thus, for example, not only to a particular set of countries but all countries. As such, multilevel models are superior to ignoring the group membership, aggregating the data on group-level, or estimating separate regressions for each group (De Leeuw and Kreft 1986, Hofmann 1997, Tate and Wongbundhit 1983).

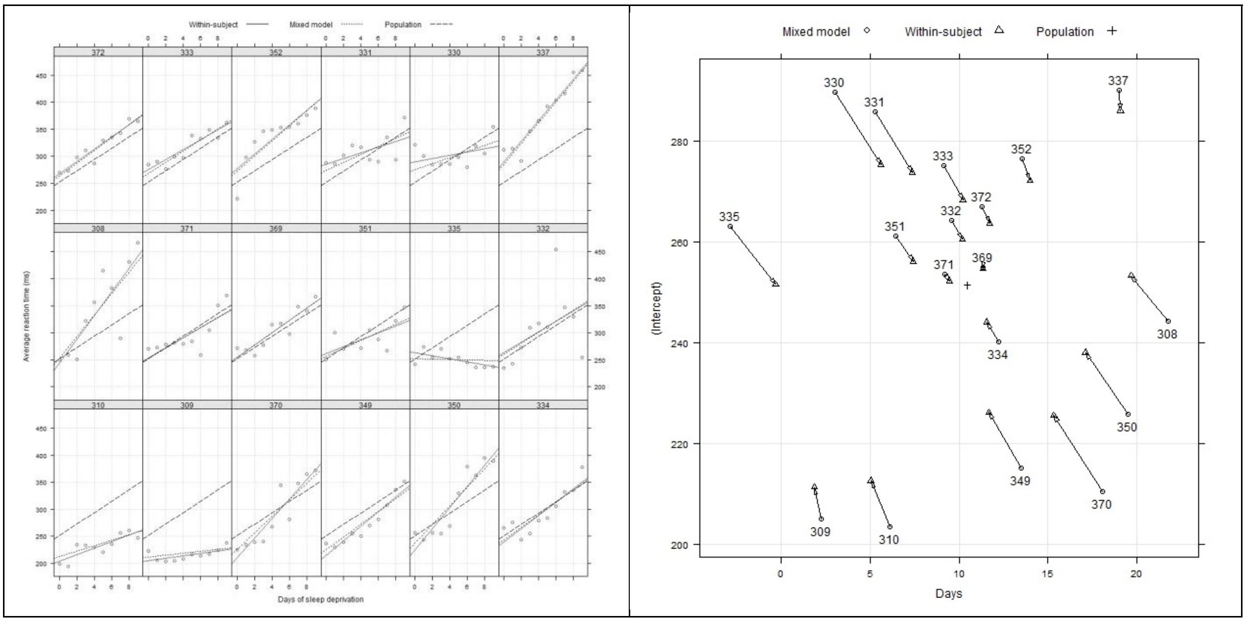
From a statistical perspective, **treating units of analysis as independent observations biases the results**. It seems obvious that observations from one group are likely to be more similar to each other than the observations from different groups (Hox 2010). Failing to account for the hierarchical structure leads to underestimation of standard errors of the regression coefficient and thus incorrect inferences and interpretation of results (Snijders and Bosker 2012). Multilevel models recognize the existence of hierarchically structured data by allowing for residual components at each level in the hierarchy by partitioning the observed variance into within- and between cluster variance (Goldstein 2011).

Further, multilevel models **control for observed and unobserved heterogeneity** on the group-level. Addressing the correlation of individual responses within groups by conditioning on covariates controls for the observed portion of heterogeneity, but there is usually unobserved heterogeneity left (Rabe-Hesketh and Skrondal 2006). Including a random intercept in multilevel models takes this dependence into account (Muthén and Asparouhov 2009).

Moreover, multilevel models have a **higher predictive accuracy** than classical regression models (Gelman 2006). Applying multilevel models is particularly useful to derive more accurate parameter estimates for a given group, which itself has only very few observations.

Therefore, multilevel models borrow information from other groups. The less precise the within-group estimate and the less variability observed across groups, the greater the shift towards the group-mean estimate (Diez-Roux 2000). This is known as “shrinkage effect” (Snijders and Bosker 2012). Figure 2.1 illustrates how the estimates that would be obtained by modeling each group individually are shrunk toward the grand mean when applying a multi-level model.

Figure 2.1: Visualizing shrinkage in multilevel models



Note: Example (data and R code) adapted from Bates (2010, pp. 72, 73). Left figure: Each graph indicates the observed data for one individual in the exemplary study. While the solid line indicates the within-subject predictions, the dashed line indicates those of the mixed-effects model. Right figure: This figure compares the within-subject estimates with those of the mixed-effects model. The arrows run from the within-subject estimate to the conditional mode for the mixed-effects model.

Lastly, multilevel models have been proven to be **robust in case of unbalanced designs** (Longford 1987). In other words, in case individual observations vary per group or measurements for repeated observations are not equally spaced, multilevel models still provide reliable parameter estimates.

2.3 Methodology

The objectives of this literature review are threefold. First, to highlight research areas where multilevel data regularly occurs and where the applications of multilevel models have had an impact on the implications derived for marketing practice, we structure the existing studies applying multilevel modeling approaches into distinct areas. Second, to give detailed insights into hierarchical compositions of data, we highlight which levels of analyses are predominantly modeled within each research area as well as how they differ between them. Third, to give guidance for future research analyzing multilevel data, we derive potential research questions as brought forward by seldom used hierarchical compositions and limitations of existing studies.

To identify marketing areas where multilevel models have been applied, we **apply a three-step procedure**. First, we identified articles in the major marketing journals applying multilevel models. Second, we examined those articles and the hierarchy of the data analyzed in detail. Third, we derive a structure which groups the articles into distinct categories according to their research area.

Our **literature search** covers articles published between 1990 and 2013 in the Journal of Marketing, Marketing Science, the Journal of Marketing Research, the International Journal of Research in Marketing, and the Journal of the Academy of Marketing Science. We did a full-text search on multiple electronic databases, such as the journals' electronic archives, EBSCO Business Host Premier, and Science Direct. Based on interviews with five senior researchers from different disciplines who have been regularly applying multilevel models in the past, we defined the following search terms: "multilevel", "hierarchical", "random coefficient", "random effect", "mixed model", "disaggregated data", and "heterogeneity". Further, we examined citations in the articles we found. Three marketing scholars reviewed those articles and gathered details on their methodological approach. Studies which did not apply multilevel modeling were excluded. Among all articles, 174 articles which applied a multilevel modeling approach were identified.

Next, the 174 **articles were examined in detail** to identify the main research question, data analyzed, the levels of analysis, estimation procedures applied, as well as the dependent variable(s).[2] 22 studies which apply a multilevel modeling approach but contribute from a methodological point of view to marketing literature were excluded.[3] Further, five articles were excluded as it was not possible for the researchers to reach an agreement concerning the number of levels (Bronnenberg and Sismeiro 2002, Chandukala et al. 2011a, Moon et al. 2007, Park and Gupta 2011, Wedel and Zhang 2004). In the discussion, we highlight challenges of identifying multilevel studies and levels and propose guidelines for a standardized terminology and way of reporting methodological details on multilevel models in marketing. Finally, 147 articles remained in this literature review.

Structuring the studies is a necessary task to work out marketing research areas for which the application of multilevel models are particularly useful. To do so, we applied a three-step procedure.

First, we standardized the naming of the level units. Thus, the levels had to be grouped to more general units, e.g., all individuals, such as persons, customers, consumers, households, and professions were treated as one class of levels (see Table 2.1).[4] Three marketing scholars accomplished this task independently. Their categorizations match almost perfectly. In case of

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[2] A table with detailed search results for each article in this review is available upon request.

[3] We found several papers that enhance marketing research by evaluating existing methods and developing appropriate modeling techniques within a multilevel framework. This is done, for example, in the contexts of treating heterogeneity in structural equation models (Ansari et al. 2000b), comparing hierarchical Bayes and finite mixture conjoint analysis (Andrews et al. 2002), or examining socially desirable response tendencies in an international setting (Steenkamp et al. 2010a). Further studies with a methodological focus are: Ailawadi et al. (1999), Andrews and Currim (2005), Andrews et al. (2008), Andrews and Currim (2009), Baumgartner and Steenkamp (2001), Chib et al. (2004), Chintagunta and Dubé (2005), De Jong et al. (2008), Gönül and Srinivasan (1993), Haaijer et al. (1998), Islam et al. (2007), Liechty et al. (2005), Moore (2004), Otter et al. (2004), Park and Gupta (2012), Steenburgh et al. (2003), Tellis and Chandrasekaran (2010), Ter Hofstede et al. (2002a), Zeithammer and Lenk (2009).

[4] It is therefore possible that according to the standardized names employees can appear as level-one as well as level-two units referring to, e.g., salespersons nested in sales managers, or sales managers nested in directors.

discrepancies between the three marketing scholars, we followed the majority voting.

Table 2.1: Identification of levels in the studies

Level specification	Included units of analysis
Level 1, level 2	
Time	Repeated observations (e.g. purchase occasions. weekly sales, etc.); measured per hour, day, week, month, quarter, or year
Level 1, level 2, level 3	
Product	Brand, category, (product) choice sets, product profiles, product-specific promotion, product-specific advertisement, page view, scenario, broad-casting time, transaction, store visit
Customer	Consumer, customer, household, individual, physician, visitor (on a page), homeroom, concert audience
Employee	Salesperson/ frontline employee, team (of employees), (BU) manager, (BU) director, professor
Firm	Firm, store, chain, retailer, (sales) branch, department, school/ university, orchestra
Level 2 and level 3	
Geographic region [a]	
▪ National region	ZIP-area, national region, cities
▪ Country	Country
Level 3	
industry	Industry

Note: [a] We distinguish between national region and country as unit of analysis as all studies accounting for country as a separate level of analysis are in specific analyzing data within an international context, whereas studies accounting for national regions analyze data in a national context.

Second, three marketing scholars assigned the multilevel studies to different research areas. Our initial focus was on all two-level studies. To facilitate this task, we presented a subset of papers to the marketing scholars. A subset consisted of those papers which were based on data with the same level-one and level-two units. The marketing scholars were asked to identify the research area of those papers. After evaluating all papers, we had two pieces of information: (1) which papers were grouped together and (2) the assigned research areas. Based on the former information, we derived whether any two papers were assigned to the same group. In case of discrepancies between the three marketing scholars, we followed the majority voting. Based on the latter information, we created a list with all the research areas assigned by the marketing scholars and asked a fourth marketing scholar without prior knowledge on the papers to consolidate this list.

Third, we repeated the procedure with five different marketing scholars. But this time, we handed them the consolidated list with research areas and asked them to assign the papers to one of them. We repeated this step for the three-level studies. Our results show only very few discrepancies between the five marketing scholars. In case of discrepancies between the five marketing scholars, we followed the majority voting.

This approach led us to the **grouping of the studies according to five major marketing research areas:** (1) new product success, (2) consumer preferences, (3) customer retention, (4) marketing strategy, and (5) internal marketing. The grouping is shown in Table 2.2.

Table 2.2: Grouping of studies into distinct marketing research areas

Marketing research area	Number of 2-level studies	Number of 3-level studies	Sum of studies
New product success i.e., studies on new products, diffusion and innovation, product adoption	17	5	22
Consumer preferences i.e., studies on consumer choice, purchase decisions	36	3	39
Customer retention i.e., studies on customer satisfaction, loyalty, relationships	17	7 (8)[a]	24 (25)[a]
Marketing strategy i.e., studies on marketing mix decisions, segmentation, targeting, and positioning, product branding	40	5	45
Internal marketing i.e., studies on organizational identification, work environment, organizational change	15	2 (3)[a]	17 (18)[a]
Sum	125	22 (24)[a]	147 (149)[a]

Note: [a] In two studies, both a two- and a three-level model are applied; those studies are listed twice in the results table in the following chapter (i.e., Lam et al. (2010), Liu (2007)). Meta studies applying multilevel modeling are also included in this table.

In the following we will present the results of our literature review. Thereby, we will give a brief overview of the marketing research area and its relevance to marketing and highlight the hierarchical composition of the data used. By illustrating some of the papers in more detail, we will point out the relevance of applying such models in the respective research area. At the end, we give an overview of future research questions which can be answered by applying multilevel modeling approaches. Two-level models will be presented in a matrix format indicating the levels used. As this matrix format is not applicable to the three-level studies, they will be shown in a separate table in each sub-chapter covering one research area.

2.4 Results

2.4.1 Multilevel studies in the research area of new product success

The **introduction of a new product in the market is one of the most crucial activities of a firm** (e.g., Gielens and Steenkamp 2007). Analyzing determinants of the acceptance of new products or innovations gives important insights into what drives customers' adoption behavior. With these insights, practitioners are able to set up effective marketing campaigns and allocate resources accordingly in the early stages of a product's lifecycle. An overview of the current state of research in this area is provided by Peres et al. (2010).

Accounting for **different levels of analysis is important as most of the studies in this research area deal with longitudinal data**. Accordingly, time is the predominant level-one unit. The majority of studies deals with data where time is nested in products (see Table 2.3). Similarly, other studies analyze new product success on country-, firm-, or customer-level. Few studies refer to products or customers as level-one units of analysis nested within firms or geographic regions (i.e., national regions or countries).

Multilevel models allow researchers to get detailed insights on the context's impact of new product success. Analyzing 31 consumer durables over a time of 74 years, Van den Bulte (2000) finds an increase in diffusion speed over the last centuries which besides others can be explained by product characteristics. Further, several models have been developed for forecasting new product sales specifically accounting for product-level covariates such as prelaunch announcements to explain differences across products (Moe and Fader 2002). Steenkamp et al. (1999) analyze antecedents of consumer innovativeness and distinguish consumer difference variables (e.g., consumer ethnocentrism) and national cultural variables (e.g., uncertainty avoidance).

Table 2.3: Two-level studies on new product success

Level 2 units Level 1 units	Product	Customer	Em-ployee	Firm	National region	Country
Time	Chintagunta and Lee (2012), Krishnan et al. (2012), Lenk and Rao (1990), Moe and Fader (2002), Van den Bulte (2000)	Manchanda et al. (2008), Van Ittersum and Feinberg (2010)		Prabhu et al. (2005), Sorescu et al. (2003)		Desiraju et al. (2004), Neelamegham and Chintagunta (1999)
Product				Yli-Renko and Janakiraman (2008)		Van den Bulte and Stremersch (2004)
Customer					Choi et al. (2010)	Steenkamp et al. (1999)
Employee						
Firm						

Note: We found two meta studies within the area of new product success dealing with hierarchical data in the sense that measurements are nested within studies (Arts et al. 2011, Troy et al. 2008).

Analyzing data with more than two levels enables researchers to derive even more comprehensive implications on new product success (see Table 2.4). For example, Gielens and Steenkamp (2007) study consumers' acceptance of new products in the first four quarters after product launch and account for different sources of variations including product-related and consumer-specific drivers. It is to note that the authors also add an international perspective to their study. However, as their data comprises sales from only four countries, they do not model those as an additional level, but estimate separate models for each country.

Table 2.4: Three-level studies on new product success

Study	Level-one units	Level-two units	Level-three units
Gielens and Steenkamp (2007)	time	customer	product
Stremersch and Lemmens (2009)	time	product	category
Van Heerde et al. (2004)	time	product	firm
Gielens (2012)	product	product	firm
Talukdar et al. (2002)	time	product	country

2.4.2 Multilevel studies in the research area of consumer preferences

Understanding the reason behind the consumer's purchase decision is one of the most relevant questions analyzed in marketing. For the success of a product, it is important to link consumers' preferences to actual consumption behavior and expenditures (e.g., Biswas et al. 2014, Du and Kamakura 2008). Thus, most studies focus on how customers choose a specific product given a set of alternatives. Knowing about customer preferences gives insights into their choice behavior which is relevant for predicting and influencing product demand.

When **dealing with consumer preferences and consumption decisions, data in most cases has an inherent hierarchical structure.** Products are necessarily nested within customers. Looking at the hierarchical structures of the data analyzed in this research area reveals that studies cover a wide range of level-one units, such as time, product, choice sets, and customers (see Table 2.5). However, these units are predominantly nested within customers at level two. Only a few studies analyze the impact of characteristics on product, firm, and national region at level two.

The complexity of customer's purchase decisions leads researchers to draw inferences based on hierarchical data structures. Inman et al. (2009) disentangle how category-level characteristics (e.g. purchase frequency and displays) as well as customer-level effects (e.g., household size and gender) influence the customer's in-store decision making. Further, Yang and Allenby (2003) find support for the varying influence of geographically and demographically defined networks on consumer preferences for Japanese-made cars. Laroche et al.

(2007) analyze the influence children have on the family's purchase decisions accounting for individual-level (e.g., ethnic identification) and family-level (e.g., generational dissonance) characteristics.

Table 2.5: Two-level studies on consumer preferences

Level 2 units Level 1 units	Product	Customer	Employee	Firm	National region	Country
Time		Ainslie and Rossi (1998), Boatwright and Nunes (2001), Goettler and Clay (2011), Manchanda et al. (1999), Prasad et al. (2008)				
Product		Allenby et al. (2004), Arora et al. (1998), Bucklin and Sismeiro (2003), Chintagunta (1992), Chintagunta et al. (1991), Danaher et al. (2011), Gilbride et al. (2008), Gupta et al. (1997), Inman et al. (2009), Jedidi et al. (2003), Kim et al. (2002), Klapper et al. (2005), Wuyts et al. (2004) *The following studies analyze product choice sets nested in customers:* Allenby and Ginter (1995), Arora (2006), Bradlow and Rao (2000), Chandukala et al. (2011b), Gilbride and Allenby (2004), Haaijer et al. (2000), Liechty et al. (2001), Michalek et al. (2011), Shively et al. (2000), Wuyts et al. (2009), Yang et al. (2002)				
Customer	Du and Kamakura (2008)	Arora and Allenby (1999), Laroche et al. (2007)		Kamakura and Schimmel (2013), Raju et al. (2010)	Sismeiro and Bucklin (2004), Yang and Allenby (2003)	
Employee						
Firm						

Note: Ainslie and Rossi (1998) apply a cross-classified multilevel model where time is level one and households and categories are level two. We indicated it as time nested in customers. Wuyts et al. (2009) deal with preferences in partner selection in B2B information service markets.

Although **three-level studies are rare in this research area**, adding another level of hierarchy offers an even more detailed understanding of effects on consumer preferences and product choice (see Table 2.6). For example, Steenkamp et al. (2010b), study the effect of marketing and manufacturing factors on consumers' willingness to pay. Applying multilevel modeling, they disentangle, for example, the impact of advertising campaigns on consumers' willingness to pay controlling for heterogeneity on the consumer-level (e.g., category involvement), on product-level (e.g., packaging), and country-level (e.g., GDP).

Table 2.6: Three-level studies on consumer preferences

Study	Level-one units	Level-two units	Level-three units
Seetharaman et al. (1999)	time	product	customer
Chang et al. (1999)	time	product	customer
Steenkamp et al. (2010b)	customer	product	country

2.4.3 Multilevel studies in the research area of customer retention

Customer retention is one of the key activities of a customer-centric business. Enhancing customer retention is essential to establish a competitive advantage, gain market share, and increase firm performance (e.g., Woodruff 1997). Firms, which pursue such a strategy, aim to establish valuable relationships with customers and look at various indicators such as customer satisfaction and loyalty to monitor their success (e.g., Gustafsson et al. 2005, Rego et al. 2013). Meeting the consumers' expectations and thus enhancing customer satisfaction with the product influences repurchase intentions and leads to increased customer loyalty.

Within this research area, essentially the **customer as level of analysis plays the most important role** (see Table 2.7). We find that except for two studies, the customer is either the level-one or level-two unit. Time, product, and customer are the predominant level-one units. Concerning level-two units, time and product are nested within customers and customers are nested in either employees or firms. One study in this research area takes an international perspective, i.e., customers are nested within countries.

Table 2.7: Two-level studies on customer retention

Level 2 units Level 1 units	Prod-uct	Customer	Employee	Firm	National region	Country
Time		Grégoire et al. (2009), Liu-Thompkins and Tam (2013), Liu (2007), Rust et al. (2011), Samaha et al. (2011), Venkatesan and Farris (2012)		Krasnikov et al. (2009a), Van Heerde and Bijmolt (2005)		
Product		Ansari et al. (2000a), Homburg et al. (2005), Lenk et al. (1996)				
Customer			Brady et al. (2012), De Ruyter et al. (2009), Homburg et al. (2009b)	Bolton et al. (2008), Homburg et al. (2010a)		Van Birgelen et al. (2002)
Employee						
Firm						

Note: Krasnikov et al. (2009a) examine the impact of CRM implementation of a firm on cost and profit efficiencies, thus customer is not a level in this study although dealing with customer relationships. Van Heerde and Bijmolt (2005) decompose revenue effects of loyalty program members versus non-members taking into account the revenue for a store (=firm-level) on a specific day (=time-level). Liu (2007) applies both a two- and a three-level model. Thus, this study is listed in Table 2.7 as well as Table 2.8.

Multilevel modeling helps to disentangle both, the impact of customer characteristics across various products and the role of external factors (e.g., country characteristics) for customer retention. For example, Liu (2007) examines the long-term impact of loyalty programs. Analyzing how the purchase frequency of customers, who are enrolled in a loyalty program, develops over time the study provides support that the growth pattern varies depending on customer-level characteristics (e.g., heavy versus light buyers). In a study on the determinants of customer satisfaction, Van Birgelen et al. (2002) show the importance of accounting for individual-level effects (e.g., service quality perceptions) as well as country-level characteristics (e.g., culture). Homburg et al. (2010a) study the complaint handling of firms examining how customer characteristics (e.g., perceived severity of a problem) and firm-level effects (e.g., quality of complaint handling design) influence the customer's perceived fairness of complaint handling.

Three-level studies in this research area predominantly examine the importance of employee-level characteristics for customer-level retention measures (i.e., satisfaction and loyalty) or focus on how firm-level indicators on customer retention vary over time and industry (see Table 2.8). For example, Homburg et al. (2009a) analyze the impact of customer-level (e.g., family status), salesperson-level (e.g., job know-how), and manager-level (e.g., training of customer-oriented interaction behavior) covariates on customer satisfaction and willingness to pay. Mittal et al. (2005) consider the influence of time-varying covariates (e.g., customer satisfaction), firm-specific effects (e.g., efficiency), and industry characteristics (e.g., Herfindahl Index) to examine the long-term impact of customer satisfaction on firm performance.

Table 2.8: Three-level studies on customer retention

Study	Level-one units	Level-two units	Level-three units
Liu (2007) [a]	product	time	customer
Homburg et al. (2009a)	customer	employee	employee
Homburg et al. (2011)	customer	employee	employee
Rapp et al. (2013) [b]	customer	firm	employee
Palmatier et al. (2006)	customer	employee	firm
Anderson et al. (2004) [c]	time	firm	industry
Gruca and Rego (2005) [c]	time	firm	industry
Mittal et al. (2005) [c]	time	firm	industry

Note: [a] The author models transactions nested in quarters nested in customers, thus time - as an exception from all other studies - is denoted as second-level unit. Further, both a two- and a three-level model is applied. Thus, this study is listed in Table 2.7 as well as Table 2.8. [b] The authors analyze hierarchical data in which customers (level one) are nested in retailers (level two) which are nested in supplier salespersons (level three). [c] These studies obtain satisfaction measures from the American Customer Satisfaction Index (ACSI) database, thus include a customer satisfaction measure on firm-level.

2.4.4 Multilevel studies in the research area of marketing strategy

In order to be successful in the market, **firms need to sell the right product to the right customer at the right time** (e.g., Li et al. 2011). Therefore, a continuous assessment of a firm's strategic decisions on its marketing mix as well as its customer segmentation, targeting, and positioning is important. Thereby, the marketing strategy of a firm also covers all efforts made concerning the brand.

Table 2.9: Two-level studies on marketing strategy

Level 2 units / Level 1 units	Product	Customer	Employee	Firm	National region	Country
Time	Ailawadi et al. (2006), Ailawadi et al. (2007), Ataman et al. (2008), Cain (2005), Chintagunta and Desiraju (2005), Montgomery and Bradlow (1999), Narayanan et al. (2004), Sriram et al. (2007), Sudhir (2001), Talukdar et al. (2011)	Dong et al. (2009), Manchanda et al. (2004), Montgomery et al. (2004), Rossi et al. (1996)		Luo and Donthu (2006), Mitra and Golder (2008), Rao et al. (2004), Srinivasan et al. (2008), Wuyts and Dutta (2008)		
Product	Schweidel and Kent (2010)	Bijmolt et al. (1998), Brown (1999), Häubl and Elrod (1999), Li et al. (2011)		Montgomery (1997), Montgomery and Rossi (1999)	Silva-Risso and Ionova (2008)	Akdeniz and Talay (2013), Leenders and Eliashberg (2011)
Customer	Wedel and Pieters (2000), Zhou et al. (2010)	Hartmann (2010)			Ter Hofstede et al. (2002b)	Bijmolt et al. (2004)
Employee						
Firm						Wu (2013)

Note: We found four meta-analysis within the area of marketing strategy (Bahadir et al. 2009, Krasnikov and Jayachandran 2008, Kremer et al. 2008, Rodriguez Cano et al. 2004) dealing with hierarchical data in the sense that measurements are nested within studies. Kiygi Calli et al. (2012) analyze whether advertising effects vary across the hours (level one) of the week (level two). According to our standardization of the naming of the level units (see Table 2.1), in this study time is level-one and level-two unit and thus, this study is not shown in this table.

As **studies in this area often rely on purchase history data**, the necessity of applying multilevel models is rather obvious. Consequently, time (i.e., purchase occasions) is the predominant level-one unit of analysis nested in products, customers or firms (e.g., retail stores). Further, product and customer appear as level-one units (see Table 2.9). On level two, all units of analysis except the employee-level are considered.

Besides analyzing longitudinal data, **multilevel modeling is applied in this research area to examine firms' marketing efforts by either looking at the impact of contextual factors on brand-level or customer-level measures of brand success.** For example, Akdeniz and Talay (2013) analyze the impact of marketing signals (e.g., advertisements, price) on box office performance accounting for product-related characteristics (e.g., production budget of the movie) as well as country-level variables (e.g., culture). Zhou et al. (2010) examine the impact of customer-level (e.g., confidence in brand origin identification) as well as brand-level covariates (e.g., foreign versus local brand origin) on customers' perceived brand value. Analyzing the impact of marketing communication productivity on shareholder value over time, Luo and Donthu (2006) find support for a positive nonlinear growth pattern which varies depending on firm-level factors (e.g., marketing managerial expertise).

Three-level studies in this area analyze the impact of factors on various levels (see Table 2.10). For example, Mitra and Golder (2006) examine the relationship between objective and perceived product quality over time, taking into account differences in quality effects across product-level variables (e.g., brand reputation) and category-level effects (e.g., purchase frequency). Krasnikov et al. (2009b) apply a growth model to analyze the financial value of branding using trademarks taking into account heterogeneity related to firm-specific characteristics (e.g., research and development intensity) as well as industry-level effects (e.g., overall demand in industry).

Table 2.10: Three-level studies on marketing strategy

Study	Level-one units	Level-two units	Level-three units
Mitra and Golder (2006)	time	product	product
Chintagunta (2002)	time	product	customer
Ataman et al. (2010)	time	product	firm
Dixit and Chintagunta (2007)	time	product	national region
Krasnikov et al. (2009b)	time	firm	industry

2.4.5 Multilevel studies in the research area of internal marketing

In recent years, multilevel models have been applied in studies dealing with **the internal firm environment**. Studies discussed so far analyze the external environment of the firm dealing with perceptions of customers or the firm's marketing strategy directed towards customers. Employees build the direct link between a firm and its customers and have been identified as important intermediary in a firm's marketing communication process (e.g., Hughes 2013). To achieve a successful marketing implementation (e.g., customer orientation, sales performance), internal marketing is concerned with empowering and motivating employees by marketing clear organizational values and a vision which is worth pursuing to all employees (e.g., Berry and Parasuraman 1992).

In any case, studies **applying multilevel analysis in this area include the employee level as units of analysis**. Thereby, several studies analyze multiple employee groups within one firm, e.g., salespersons and their managers (see Table 2.11). Rather seldom are studies which take a longitudinal perspective on employee-level measures (e.g., salesperson performance). Similarly, studies examining employee-level measures across firms and geographic regions are rare.

Table 2.11: Two-level studies on internal marketing

Level 2 units Level 1 units	Product	Customer	Employee	Firm	National region	Country
Time			Ahearne et al. (2010), Fu et al. (2010)			
Product						
Customer						
Employee			Ahearne et al. (2013a), Ahearne et al. (2013b), De Jong et al. (2004), Hughes and Ahearne (2010), Lam et al. (2010), Schepers et al. (2012), Schmitz (2013), Wieseke et al. (2009), Wieseke et al. (2008a)	Maxham et al. (2008), Palmatier et al. (2013), Sarin et al. (2012)	Wieseke et al. (2012)	
Firm						

Note: Lam et al. (2010) apply both a two- and a three-level model. Thus, this study is listed in Table 2.11 as well as Table 2.12.

Multilevel modeling is mostly applied in this research area to examine either salespersons' performance or their adoption of new practices by looking at determinants on different organizational levels. De Jong et al. (2004) analyze how individual-level (e.g., tolerance of self-management) and team-level antecedents (e.g., inter-team support) influence service climate. Wieseke et al. (2009) apply several two-level models to analyze the impact of leadership for organizational identification looking at, e.g., sales representatives nested in business unit (BU) managers or BU managers nested in regional directors. Ahearne et al. (2010) choose a multilevel model to analyze the development of salespersons' performance during a period of change and thus, are able to identify which characteristics (e.g., goal orientation) enable salespersons to better adapt to change than others.

Three-level models in his research area simultaneously disentangle the impact of covariates on multiple organizational levels (see Table 2.12). Homburg et al. (2010b) study the adoption of new technologies by salespersons accounting for effects on salesperson-, sales manager-, as well as regional manager-level (e.g., perceived usefulness, training and support respectively on all three levels). Analyzing characteristics on salesperson-, manager-, and director-level in their model (e.g., market orientation on each level), Lam et al. (2010) identify those persons in the organization which are most effective to diffuse the market orientation culture from management to frontline employees.

Table 2.12: Three-level studies on internal marketing

Study	Level-one units	Level-two units	Level-three units
Homburg et al. (2010b)	employee	employee	employee
Lam et al. (2010)	employee	employee	employee
Mittal et al. (2008)	time	employee	firm

Note: Lam et al. (2010) apply both a two- and a three-level model. Thus, this study is listed in Table 2.11 as well as Table 2.12.

2.4.6 Summary of results

Implications derived from our literature review for future research are two-fold. Results (1) give practical guidance to marketing scholars when and how to apply multilevel models and (2) show research gaps and avenues for further research within each marketing research area.

Firstly, we were able to **identify several research areas in marketing** where the application of multilevel models is appropriate due to the underlying data hierarchy. This is the first study to summarize the existing studies published in top-tier marketing journals applying multilevel models providing an understandable structuring of those papers.

Secondly, from the discussion above, we **derive rarely used multilevel data structures in each research area** providing guidance for future research. Looking at limitations discussed in some of the papers and combining them with seldom used hierarchical compositions while thinking of an "ideal-data-situation" led us to the formulation of several potential research questions of interest for future studies. An overview is given in Table 2.13.

Table 2.13: Guidance for future research analyzing multilevel data

Marketing research area	Levels ignored or rarely used in previous studies	Potential research questions as brought forward by seldom used hierarchical compositions (reference in brackets if referring to limitations discussed in existing studies)
New product success	L1: time L2: employee	How do salesperson adapt to new product introductions? (Ahearne et al. 2010); What is a salesperson's impact on new product performance in the maturity and declining stages of a product's lifecycle? (Fu et al. 2010)
	L1: firm L2: country	How do firm- and country-level effects influence firm-level takeoff of new products?[5]
	L1: time L2: product L3: country	How do cross-country spillover effects (in sales, marketing instruments, and regulation) influence international new product growth? (Stremersch and Lemmens 2009)
Consumer preferences	L1: customer L2: country	How does culture influence consumer preferences? (own consideration)
	L1: time L2: customer	How do temporal aspects such as word-of-mouth and buzz influence the interdependence of consumer preferences? (Yang and Allenby 2003)
Customer retention	L1: customer L2: product (L3: firm)	What strengthens the relationship between customer satisfaction and willingness to pay for a product? (Homburg et al. 2005)
	L1: customer L2: employee/firm (L3: employee/firm/industry)	How do customer product perceptions influence the effectiveness of salesperson customer orientation (across firms/industries)? (Homburg et al. 2011)
Marketing strategy	L1: customer L2: product	How does confidence in brand origin identification influence consumer evaluations of brand value? (Zhou et al. 2010)
	L1: product L2: region/country	How do local critics' reviews influence box office performance in several regions/countries? (Akdeniz and Talay 2013)

[5] This research question is analyzed in the study presented in chapter three.

Table 2.13 (continued)

	L1: product L2: firm	How does the effectiveness of new product advertising impact firm performance? (Srinivasan et al. 2009)
	L1: time L2: firm L3: country	How do marketing capabilities influence firm performance across countries? (Wu 2013)
	L1: time L2: product L3: customer	What is the long-term effect of quality on price and advertising sensitivity of customers? (Mitra and Golder 2006)
Internal marketing	L1: employee L2: firm	What are the effects of framing a strategic change in positive versus negative terms? (Sarin et al. 2012)
	L1: employee L2: country	How do cultural characteristics of a country influence salesperson performance? (own consideration)
	L1: product L2: employee	How do organizational identification and job satisfaction influence product success? (own consideration)
	L1: time L2: employee	How does a salesperson's relational and transactional selling strategy influence salesperson performance and what are the dynamics of these relationships?[6]
	L1: time L2: employee (L3: country)	How do salesperson adapt to intended (e.g., territory realignment) and unintended (e.g., competitor's action) changes (across countries)? (Ahearne et al. 2010)
	L1: employee L2: firm L3: country	How do firm-level and country-level factors impact organizational identification and job satisfaction of employees? (own consideration)

2.5 Discussion

During our literature review on multilevel models in marketing, we came across **three major issues** we want to discuss in this section:

(1) Across discipline and also across the studies surveyed, the **terms used to describe methodological concepts vary widely**. Also, the varying grade of detail in the documentation of empirical results makes it hard for the reader to follow some studies.

(2) We identify **extensions to multilevel modeling** which will affect the future use and application of such techniques in marketing. First, variance functions and correlation structures offer a way of relaxing model assumptions. Second, endogeneity has to be considered in multilevel models. Third, approaches such as cross-classified multiple membership models have frequently been applied in other research areas such as be-

[6] This research question is analyzed in the study presented in chapter four.

havioral or educational research, but have only very rarely been applied to marketing related questions.

(3) **Theories explaining multilevel problems** are rather scarce and underdeveloped. They seldom explain effects on all levels as well as across levels and rarely explain an outcome variable measured at the group level.

2.5.1 Terminology and documentation of multilevel models

The terminology used to refer to multilevel models is far from being consistent. In particular, we found three issues worth to discuss: (1) multiple terms are used to refer to the same approach, whereby (2) those terms not only vary across scientific disciplines, but (3) also vary within the same discipline.

First, although inherently describing the same statistical modeling approach, multilevel models have been referred to as mixed linear models (e.g., Goldstein 1986), random coefficient models (e.g., Longford 1993), hierarchical linear models (e.g., Raudenbush and Bryk 2002), multilevel models (e.g., Goldstein 2011, Hox 2010, Snijders and Bosker 2012), or mixed effects models (e.g., Pinheiro and Bates 2000).

Second, the terminology varies across disciplines. While the term multilevel model is predominantly used in most disciplines, e.g., sociology (e.g., DiPrete and Forristal 1994), psychology (e.g., Hoffman and Rovine 2007), political science (e.g., Steenbergen and Jones 2002), and management (e.g., Hitt et al. 2007), the term hierarchical linear model is often used in educational research (e.g., Raudenbush and Bryk 2002), while in econometrics it is often referred to as random coefficient model (e.g., Longford 1993, Rosenberg 1973).

Third, even within disciplines the application of terms varies. In education, for example, although predominantly described as hierarchical linear models (e.g., Raudenbush 1988), some researchers use the terms multilevel models (e.g., Dedrick et al. 2009) and random coefficient models (e.g., De Leeuw and Kreft 1986, Tate and Wongbundhit 1983). Also, the studies from the marketing area use different terms, such as hierarchical linear model (e.g., Wieseke et al. 2009), random effects model (e.g., Andrews and Currim 2009), or mixed effects model (e.g., Bolton et al. 2008). A consistent terminology would benefit researchers by improving both, understandability of the statistical approach applied as well as interchangeability of methodological developments across disciplines.

Further, the **grade of detail in the documentation of empirical results of multilevel models varies significantly**. While some authors provide comprehensive information on the model development and estimation procedure, others only provide little statistical details making it hard and sometimes impossible to follow their methodological approach. Thus, the establishment of guidelines for reporting multilevel modeling is necessary.

Following Dedrick et al. (2009) and our own experience, we **derived a list of reporting guidelines** (see Table 2.14). Ideally, researchers should follow that list as best as possible to provide a complete documentation on their methodological approach.

Table 2.14: Reporting guidelines for multilevel modeling in marketing

1. ***Model development and specification***
   - Specification of the model used (e.g., random intercept, random slope)
   - Verbal description of both fixed and random effects
   - Equation representation and verbal description of it
   - In case of longitudinal data: explanation of specification of time (e.g., linear, polynomial)
   - Information on estimation method (e.g., maximum likelihood, Bayesian methods, etc.)
   - Software used for analysis
2. ***Explanation of dataset and variables in the model***
   - Explanation of the operationalization of the dependent variable
   - Explanation of selection procedure of predictors (e.g., a priori considerations, significance tests, effect sizes, fit statistics)
   - Explanation of the set of predictor variables for each dependent variable (if necessary)
   - Explanation of each level (e.g., explicitly name the level units)
   - Discussion of interactions examined (level one, level two, cross-level interaction)
   - In case of longitudinal data: specifying time-invariant and time-varying level-one and/ or level-two predictors
   - Discussion of selection of covariance structure (e.g., by prior looking at the data, based on fit statistics, likelihood-ratio tests or significance tests)
   - Explanation of centering methods used (level one and / or level two, grand mean, group mean, other or no centering)

Table 2.14 (continued)

3. ***Data-consideration issues***
   - Providing assumption tests
   - Completeness of data: treatment of missing data (e.g., imputation, listwise deletion, etc.)
   - Discussion of outliers
   - Discussion of possible endogeneity problems
4. ***Model estimation and representation of fixed and random effects***
   - Estimation of baseline models (intercept-only model)
   - Estimation and discussion of interclass correlation (ICC) / variance explained
   - Table listing the estimated fixed and random effects of the full model (i.e., estimates, standard errors, significance tests)
   - Models with interactions: table listing estimated effects without interactions, interaction plots
   - Address convergence issues

Note: Adopted from Dedrick et al. (2009), grouped according to and supplemented by own criteria.

2.5.2 Extending multilevel models

Extensions in multilevel modeling will be important for future studies and thus should be considered when applying multilevel models. Even though many of the advances have been used in specific domains, applied researchers in marketing and practitioners have just recognized their value as widespread statistical software packages, such as R or Stata, provide canned estimation routines. Of particular interest are: (1) relaxing assumptions in multilevel modeling, (2) accounting for endogeneity in multilevel models, and (3) advances in multilevel modeling.

Relaxing assumptions in multilevel modeling

“Variance functions are used to model the **variance structure** of the within-group errors using covariates” (Pinheiro and Bates 2000, p. 206). Usually, the assumption of homoscedasticity is made indicating a constant residual variance not depending on the explanatory variables. However, heteroscedasticity may exist on level one and level two and failing to account for it can lead to a miss-specified model, incorrect parameter estimates, and standard errors. To relax this assumption, variance functions can be used to specify a, e.g., linear or polynomial dependence between the residual variance and explanatory variables. A linear dependence of the level-one residual variance on some explanatory variable X can be expressed by:

level-one variance $= \sigma_0^2 + 2\sigma_{01}x_{1_{ij}}$, while a quadratic dependence can be indicated by: *level-one variance* $= \sigma_0^2 + 2\sigma_{01}x_{1_{ij}} + \sigma_1^2 x_{1_{ij}}^2$ (Snijders and Bosker 2012).[7] The random level-one part now has two (or in the quadratic model three) parameters (σ_0^2 and σ_{01}, and σ_0^2, σ_{01}, and σ_1^2 respectively). This technique can not only be applied to residual variance on level one, but also to the intercept variance and random slope variance on level two.

Correlation structures are used to model dependence among the within-group errors (Pinheiro and Bates 2000). Correlation structures of the residuals are mainly used in time-series data (i.e. serial correlation structure) and spatial data (e.g. spatial correlation structure). In the context of multilevel models, Jones (1993) elaborates on serial correlation structures, whereas Diggle et al. (2004) discuss the importance of spatial correlation structures.

In case of time series data, the correlation function, which is referred to as autocorrelation function, can, for example, assume that all within-group errors pertaining to the same group are equally correlated (i.e., compound symmetry, Pinheiro and Bates 2000). A second example for serial correlation structures is expressing the current observation as a linear function of previous observations and additionally, including a homoscedastic noise term (i.e., Box and Jenkins models, Pinheiro and Bates 2000).

Spatial correlation structures are of importance in situation where similarity of level-two units (e.g., countries) may exist due to their geographic proximity. To represent spatial correlation structures, semivariograms are used (Pinheiro and Bates 2000). Several distance metrics can then be used with the spatial correlation structure, e.g., an exponential spatial correlation structure based on the Euclidean distance of individuals.[8] With the rising interest in modeling spatial data structures (Banerjee et al. 2003) applying multilevel models, accounting for correlation structure becomes an important issue to be considered in future studies.

[7] See Snijders and Bosker (2012, p. 120) for a reasoning of incorporating the factor 2.

[8] The Euclidean distance is defined as $d_E(\varepsilon_x, \varepsilon_y) = \sqrt{\sum_{i=1}^{r}(x_i - y_i)^2}$ (Pinheiro and Bates 2000).

Accounting for endogeneity in multilevel models

Like in single-level regression models, **regressors and random components are assumed to be independent in multilevel models**. In case of omitted variables, correlation between regressors and the errors can lead to biased estimates of model parameters as well as misspecification of the model (Kim and Frees 2006) . Whereas well established methods exist for modeling endogeneity in case of single level regression models, such an analysis is more complex in the setting of multilevel models. This is due to various random components existing at different levels of analysis.

Surprisingly, **modeling endogeneity in multilevel models has not gained as much as attention** as in case of single level regression models. However, some papers provide some guidance on the issue of endogeneity in multilevel models in general and in particular, how to control for it (Ebbes et al. 2004, Kim and Frees 2007, Spencer and Fielding 2000). However, as of today there is no ready-made implementation in any statistical software package.

Advances in multilevel modeling

Cross-classified, multiple membership, as well as cross-classified multiple membership models have only rarely been applied in marketing research. While all multilevel models discussed here have a strictly hierarchical structure, also non-(strictly)-hierarchical data can be analyzed with a multilevel model. In cross-classified multilevel data, lower-level units are cross-classified by at least two higher order units (Jayasinghe et al. 2003, Rasbash and Goldstein 1994). For example, customers can buy at the same store, but live in different areas of the city. Cross-classified structures have also been applied to appropriately model social relations (Snijders and Kenny 1999). Another type of complex structure is that of multiple memberships. Multiple memberships refer to data where lower level units can be members of more than one higher level unit simultaneously (Chung and Beretvas 2012, Luo and Kwok 2012). For example, customers may buy at different stores and can thus not be assigned exclusively to one higher-level unit. Cross-classified multiple membership models are a combining the two aforementioned data structure. Those models are mostly used in educational and behavioral research (Grady and Beretvas 2010, Leckie 2009), however, with the increasing research efforts to disentangle the importance of a consumers' social ties this approach may offer a fruitful avenue for future research (Tranmer et al. 2013).

Further, **multilevel mixture models** have gained a lot of interest across disciplines (Lenk and DeSarbo 2000, Muthén and Asparouhov 2009). They are also referred to as finite mixture random effect models or multilevel latent class models. In mixture models, individuals are grouped into a number of classes without knowing the actual group affiliation of the individuals. Conventional growth models are multilevel random effect model in nature as intercept and slopes vary across individuals. Combining growth and mixture models, growth mixture models (GMM) allow for differences in growth parameters across unobserved subpopulations by using latent trajectory classes (Jung and Wickrama 2008). Latent class growth analysis (LCGA) is one kind of GMM. Allowing for homogenous growth trajectories within one class, LCGA requires the variance as well as covariance parameters for the growth factors within one class to be fixed to zero (Jung and Wickrama 2008).

Multilevel structural equation modeling (MSEM) is applied if both, measurement error is an important issue within a study and the data is hierarchically structured (Lee and Tsang 1999, Marsh et al. 2009, Muthén 1994, Rabe-Hesketh et al. 2004, Yau et al. 1993). Besides, MSEM corrects for sampling error by modeling the group component of a level-one variable as latent variable (Preacher et al. 2011). Contrary to that, traditional multilevel models use group means to separate effects of level-one variables into within and between components (Preacher et al. 2011, p. 163, Raudenbush and Bryk 2002). Further, MSEM separate the between and within part of all variables, whereas traditional multilevel models conflate within- and between-level components, i.e. the level-one effects within clusters and between clusters are implicitly constrained to be equal (Preacher et al. 2011, Zhang et al. 2009). It has also been shown that traditional multilevel level models can be parameterized as structural equation models (Bauer 2003, Curran 2003, Mehta and Neale 2005). Summing up, MSEM provides a comprehensive framework to model even more complex research settings by allowing to control for observed and unobserved heterogeneity in both, observed and latent variables. An example from our literature review applying MSEM is Wieseke et al. (2012).

By applying the discussed advances in multilevel modeling, **substantive research questions can be answered in the marketing field where traditional multilevel models would reach their limits.** Table 2.15 gives and overview of potential research questions.

Table 2.15: Research questions for advanced multilevel modeling approaches

Advanced multilevel modeling approaches	**Potential research questions**
Cross-classified models	How do areas of residence and store-level effects influence consumer purchase decisions? [a]
Multiple membership models	How do store-characteristics influence consumer purchase decisions controlling for customers visiting multiple stores? [b]
Cross-classified multiple membership models	How do areas of residence and store-level effects influence consumer purchase decisions controlling for customers visiting multiple stores? [c]
Multilevel mixture models	Does grouping customers in latent segments explain customer purchase decisions controlling for store-level effects?
MSEM	How do customer and salespeople characteristics (manifest and latent, e.g., age and motivation) determine customer satisfaction and complaint behavior?

Note: [a] Customers visiting the same store live in different areas of residence; [b] Customers buy at multiple stores; [c] Customers visiting the same store live in different areas while customers also visit multiple stores.

2.5.3 Multilevel theories

Compared to the statistical, methodological, and computational advances made in the area of multilevel models, **multilevel theories explaining multilevel problems are rather underdeveloped** (Hox 2010). Two issues are important and should be considered by future research: (1) the complexity of an appropriate theory, and (2) dealing with an outcome variable on the group level.

First, **theories need to explain individual-level, group-level as well as cross-level interactions** and thus are rather complex. In specific, they have to explain why individuals are influenced differently by characteristics of the higher level units. Thus, researchers have to make theoretical assumptions concerning group membership and operationalization (Hox 2010). In one of few attempts, Chan (1998) develops a composition model for organizing constructs and theories in multilevel research.

Second, so far, **it has widely been neglected to view the influence of individuals on the group on a theoretical basis** as the dependent variable mostly is on the lower-level. Croon and van Veldhoven (2007), for example, illustrate an analytical procedure dealing with an outcome variable measured at the group level. Future research may address these limitations and further develop multilevel theories.

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3 A Close Look at the International Takeoff of New Products - The Relationship Between Firm- and Category-Level Takeoff

Abstract

It is essential for firms to predict the success of new products early. Thus far, studies have only analyzed the takeoff of new product categories. This paper introduces the concept of firm-level takeoff as a more precise measure for predicting and benchmarking the success of new products across various country markets. An analysis of 428 broadband Internet operators in 81 countries reveals the relationship between firm-level and category-level takeoff. The impact of the competitive setting on firm-level takeoff across countries with different economic statuses is also analyzed. A random coefficient discrete-time hazard model is applied, and the results indicate the following findings: (1) Firm-level takeoff depends on a firm's decision to enter a market before or after category-level takeoff. (2) The impact of this decision is moderated by the time difference between a firm's market entry and category-level takeoff. (3) Fewer competitors increase the likelihood of reaching firm-level takeoff in countries with a lower economic status, whereas this effect is negligible in other countries. Theoretical as well as managerial implications are discussed in detail.

Keywords: *Takeoff, cross-country analysis, competition, random-coefficient discrete-time hazard model*

Publication note: A previous version of this article has been submitted to Marketing Science and is currently with the authors for a first revision. Co-authors of this paper are Markus Meierer and René Algesheimer.

3.1 Introduction

It is **essential for firms to predict the success of new products early**. Product managers want to know whether and when to enter a market with their product, whether to further invest in their product in an existing market, and whether and when to take a product off the market depending on recent market conditions. Product takeoff has been introduced as an instrument to support the decision making of product managers in these situations.

Takeoff is widely recognized as the first critical milestone after product launch. It is defined as the point of transition from the introduction stage to the growth stage of a product's life cycle and is characterized by the first large increase in sales (Golder and Tellis 1997). Existing research examines various product categories nationally and internationally (e.g., Agarwal and Bayus 2002, Tellis et al. 2003). Although it is widely accepted that such predictions vary depending on a firm's context, research has neglected this aspect. This is the first study to analyze takeoff at the firm-level.

We take into account the **variation of firm-level sales trajectories within a category** to reveal the relationship between firm- and category-level takeoff. Thus, we consider both a firm's strategic decision to enter before or after category-level takeoff and the exact timing of the market entry in relation to category-level takeoff. This approach enables us to compare the relevance of this metric to the widely studied first mover and early follower advantages (e.g., Bowman and Gatignon 1996, Robinson and Min 2002, Varadarajan et al. 2008).

Competition also plays a major role for takeoff. The number of competitors entering a market at a specific time has been used in prior studies and has been deemed an important factor that drives product success. Islam and Meade (2011) highlighted the importance of competition for category-level takeoff. By modeling the impact of competition on firm-level takeoff, we are able to identify its influence during the introductory phase of a firm's newly launched product.

It is also important to consider **heterogeneity at the country level**. Recent studies on category-level takeoff have shown that developed countries have higher penetration potential and thus have a lower mean time to takeoff compared with developing countries (e.g., Dekimpe et al. 2000a, Dekimpe et al. 2000b, Stremersch and Lemmens 2009, Van Everdingen et al. 2009). Taking a firm-level perspective, we consider the economic status of a country and model the cross-level interaction of a country's economic status and a firm's number of competitors.

Distinguishing between firm- and category-level takeoffs in a cross-national setting, our study answers the following **research questions**:

1. Does firm-level takeoff depend on category-level takeoff?
2. Does competition influence firm-level takeoff?
3. Does the economic status of a country influence firm-level takeoff?

By answering these questions, we determine which firm-level and country-level characteristics affect the probability of a new product's success.

Our study **differs from previous literature in several ways**. First, this is the first study to apply the concept of takeoff to firm-level data. We use quarterly subscriber rates of 428 broadband Internet operators across 81 countries from 1996 to 2011 covering the product lifecycle of broadband Internet services from its launch until today. Our dataset includes the subscriber rates of 74.9% of all broadband Internet operators worldwide. Second, this study emphasizes the effect of country-specific category-level takeoff as an indicator of individual firms' success. Third, this is the first study to introduce the timing of market entry in relation to category-level takeoff as a new metric to predict new product success. Fourth, we control for a variety of firm-level and country-level determinants. Finally, by applying a random coefficient discrete-time hazard model, we address the shortcomings of previous studies by accounting for heterogeneity at the country level, and we are able to model cross-level interaction effects.

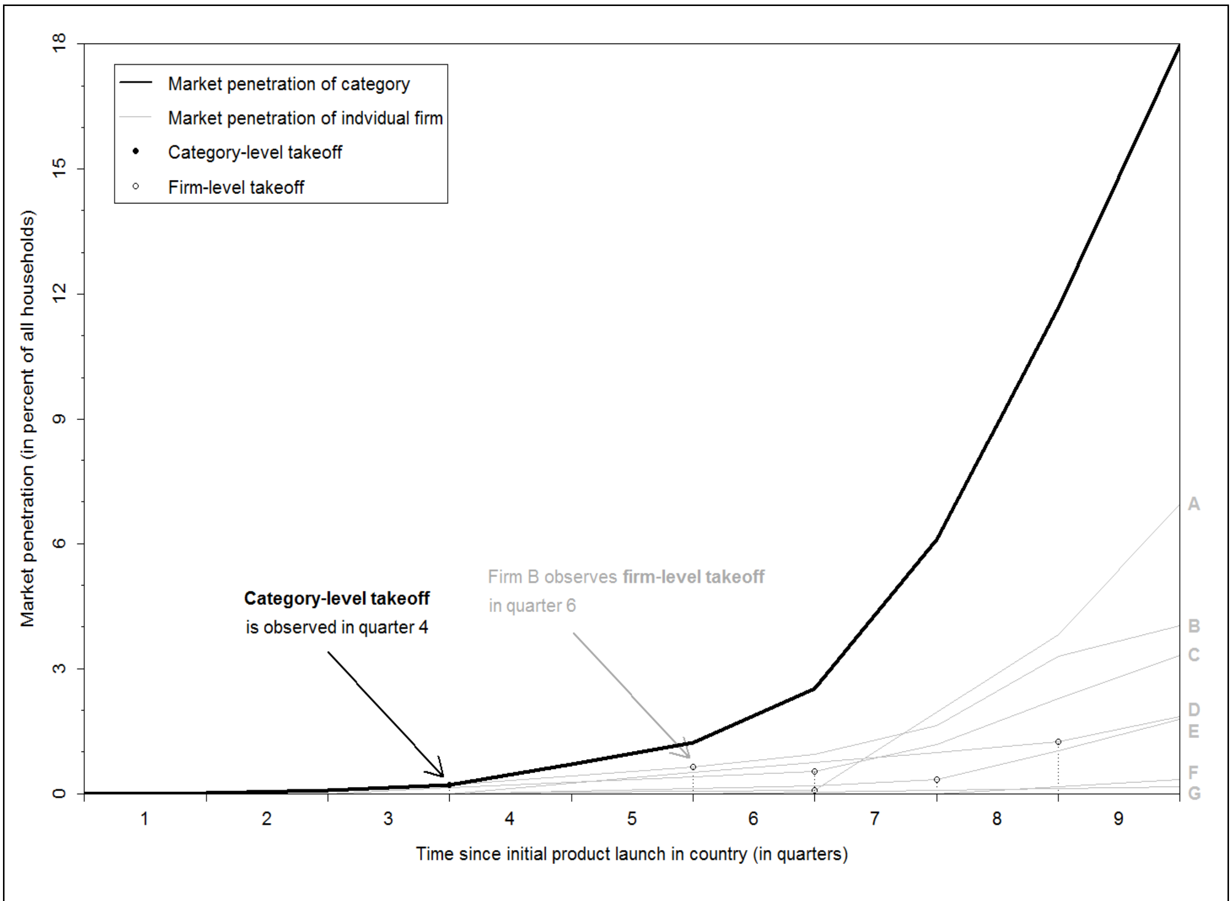
Our **main empirical findings** include the following. We find that firm-level takeoff depends on a firm's decision to enter a market before or after category-level takeoff. For firms that enter the market before category-level takeoff, the likelihood of firm-level takeoff increases with later entry. We also find that the first mover advantage recedes behind the effect of a firm's decision to enter a market before category-level takeoff if the latter is not reached soon after launching operations. Regarding the number of competitors, we find a varying influence across countries. A lower number of competitors increases the likelihood of reaching firm-level takeoff in countries with lower economic status. This effect is negligible in countries with higher economic status.

The **remainder of this paper** is organized as follows. In the second section, we argue for the importance of taking a firm-level perspective and we introduce firm-level takeoff. In the third section, we explain the underlying informational cascade theory and generate the hypotheses. In the fourth section, we discuss the modeling framework, which builds upon a random coefficient discrete-time hazard model. In the fifth section, we present the data. In the sixth section, we outline the results in detail. In the seventh section, we conclude by illustrating managerial implications, and we offer suggestions for further research.

3.2 Firm-level takeoff

The **importance of taking a firm-level perspective** lies in considering firm-specific variation within a category. We illustrate this point for an exemplary country market in Figure 3.1. The black curve indicates the cumulative number of adopters within a new product category. Previous studies on takeoff have adopted this perspective (Golder and Tellis 2004, Tellis et al. 2003, Van Everdingen et al. 2009). Markovitch and Golder (2008) were among the first to highlight the importance of going beyond the category-level perspective, but they considered only category-level takeoff in their analyses. However, pooling the data at the category level omits firm-level heterogeneity. This problem becomes evident when examining the firm-specific developmental trajectories presented in gray. Although some firms have had initial success in promoting their offerings (firms A to E), others have not yet reached firm-level takeoff (firms F and G). Some of these latter firms will never reach firm-level takeoff. Because they lack a sufficiently large market share to be profitable they will eventually exit the market.

Figure 3.1: Growth of broadband Internet subscribers in an exemplary country



A second characteristic also becomes evident: the **time firms need to reach firm-level takeoff may vary widely**. To address these issues and to overcome the limitations of a category-level perspective, we adapt the principle of “zooming in” (Goldenberg et al. 2009) to obtain a more precise and accurate measure of new product success by focusing on the firm as the unit of analysis.

Knowledge regarding firm-level takeoff is of great **managerial importance**. Whereas category-level takeoff is an indication of general acceptance by consumers (Chandrasekaran and Tellis 2007), firm-level takeoff provides insights into whether the segmentation, targeting, and positioning of a firm's product was or will be successful. Furthermore, firm-level takeoff provides a more accurate indicator of how a firm can adjust its resource allocation as the product enters its growth phase (Van Everdingen et al. 2009). Calculating firm-level takeoff also allows for benchmarking among competitors. Managers can use their combined knowledge of firm- and category-level takeoff to make more informed decisions about whether to take a product off the market (Tellis et al. 2003).

3.3 Theoretical framework and hypothesis development

3.3.1 Informational cascade theory

Informational cascade theory has been used in previous research to describe the diffusion process in a product's life cycle (e.g., Berndt et al. 2003, Golder and Tellis 2004). Informational cascades occur in a setting of sequential choices when consumers observe the behavior of others and consequently make the same choice while ignoring their own private information (Banerjee 1992, Bikhchandani et al. 1992, Bikhchandani et al. 1998). In a purchase setting, informational cascades can drive the decision-making process as follows: after some people have initially adopted a new product, they pass on their information to others, who eventually make the same purchase decision despite the presence of viable alternatives. These cascades stem from rational inferences based on limited information, resulting in an imitation process (Easley and Kleinberg 2010). This dynamic applies to the new product category in general as well as to the new product offering of a specific firm.

Informational cascades explain **adoption patterns before or after takeoff**. Before takeoff, informational cascades are quite fragile. Because the adoption decision is based on the initial decisions of a small number of early adopters rather than the cumulative decisions of all adopters, it can be easily influenced by new information. Once a substantial number of consumers adopt a new product, awareness of the increasing number of adopters outweighs the personal information of other consumers, who then decide to purchase as well (Duan et al. 2009). Golder and Tellis (2004) posit that informational cascades can depress sales prior to takeoff, sharpen the takeoff of new products, and exaggerate product growth after takeoff.

Building upon informational cascade theory, we hypothesize the impact of a firm's strategic decision to enter before or after category-level takeoff on the probability that the firm's sales will take off. Based on this theory, we further derive a hypothesis regarding the impact of competition on a firm's takeoff across countries.

3.3.2 Does firm-level takeoff depend on category-level takeoff?

Previous studies have proven the usefulness of category-level takeoff as a measure to predict success for categories in national as well as international contexts (e.g., Agarwal and Bayus 2002, Golder and Tellis 1997, Tellis et al. 2003, Van Everdingen et al. 2009). This concept has been successfully applied in practice to evaluate and predict the success of a new product category in its testing and launch phase (Foster et al. 2004).

In **informational cascade theory**, category-level takeoff signals the point at which the informational cascade has overcome its fragility. Reversing the information cascade at this point is highly unlikely. Observing the increasing number of adopters dominates the consumer's personal information and eventually leads to a purchase decision. A firm entering before category-level takeoff faces great uncertainty because a reversal of the informational cascade can occur at any time. A firm that enters after category-level takeoff can profit from the momentum of the informational cascade.

The **results of previous research are mixed**. Studies have found that entering in the early stages confers market share advantages (Lilien and Yoon 1990, Shankar et al. 1999). However, other authors highlight the advantages of postponing market entry to later stages. In particular, they highlight the importance of educating consumers about the added value of the new product or service (Bowman and Gatignon 1996).

Following this point and arguing that category-level takeoff is a strong signal that the informational cascade has gained substantial momentum, **we propose the following**:

H1.1: Firms entering after category-level takeoff have an increased probability of reaching firm-level takeoff.

According to informational cascade theory, **cascades can depress sales prior to takeoff**. If a firm decides to enter immediately after the initial product launch in a market, the informational cascade is fragile, and the uncertainty regarding product success is high. A firm that enters soon before category-level takeoff occurs is more likely to be successful as increasing information on consumer acceptance of the new category becomes available, reducing the probability of an informational cascade reversal. Thus, we propose the following:

H1.2a: For firms entering before category-level takeoff, the probability of firm-level takeoff increases the closer the market entry is to the category-level takeoff.

After category-level takeoff, a firm can profit from the momentum of the information cascade. However, as soon as maturity is reached, the information cascade can lead to reverse sales growth (Golder and Tellis 2004). Moreover, the literature has shown that early entrants may create entry barriers that decrease the probability of reaching firm-level takeoff (Han et al. 2001, Karakaya and Stahl 1989). Thus, a firm is more likely to reach firm-level takeoff when it enters shortly after category-level takeoff. We thus propose the following:

H1.2b: For firms entering after category-level takeoff, the probability of firm-level takeoff decreases the farther the firms' entry is from the category-level takeoff.

3.3.3 Do a firm's competition and a country's economic state influence the time to firm-level takeoff?

The **number of competitors is a time-varying characteristic** that reflects the degree of competition in a market. Previous research has highlighted the importance of considering the competitive situation in a market (e.g., Fischer et al. 2010, Islam and Meade 2011). In practice, competing firms strive for the same targets, such as enlarging their customer base, increasing their profits, and gaining a market share. Thus, the number of competitors in a market must be considered an important factor that drives the success of new products.

According to **informational cascade theory**, only a small number of people are responsible for the initial adoption decision. For a firm, inducing an initial set of people to adopt the product is more difficult when more competitors are in the market because a higher number of firms share the same small number of consumers. Thus, it is easier for firms to kick-start an informational cascade when fewer competitors are in the market. This reasoning is supported by the market share theorem (Bell et al. 1975), which assumes that market share is inversely related to the number of competitors in a market. A product or service is likely to become interchangeable when more competitors are present. Thus, the time to firm-level takeoff is likely to be determined by the number of competitors. If only a few competitors are present, the market potential and growth rate speed are expected to be higher.

The **results of previous research are mixed**. In their study of pharmaceutical brands, Fischer et al. (2010) find that the time to peak sales is shorter when fewer competitors are present in the market. In contrast, Islam and Meade (2011) find a positive effect of competition: the speed of diffusion increases with the number of competitors. Using the telecommunication industry as an example, they argue that competition provides additional incentives to innovate, reduces costs, and eliminates distorted prices.

There is also evidence that **variation among countries must be considered** to determine the effect of competition precisely (Dekimpe et al. 2000a, Tellis et al. 2003). Studies including non-industrialized countries are particularly rare (e.g., Dekimpe et al. 2000a, Dekimpe et al. 2000b, Stremersch and Lemmens 2009, Van Everdingen et al. 2009) and there is high demand for further research in this area (Peres et al. 2010). There is initial evidence at the product category level that firms in developing countries need a period that is 17.9% longer, on average, to reach peak sales (Talukdar et al. 2002). The mean time to category-level takeoff is also lower for developed countries (Chandrasekaran and Tellis 2008).

Extending existing research, we assume that there is a **cross-level interaction** between the state of development of the country and the number of competitors in the market. Building upon empirical evidence showing considerable variation in the time to category-level takeoff across different product categories (Agarwal and Bayus 2002) and countries (Tellis et al. 2003), we assume that this variation also holds for firm-level takeoff. This variation may be explained by the varying impact of competition in industrialized and non-industrialized countries. Developed countries offer certain advantages, such as larger market potential (Desiraju et al. 2004).

In **summary**, we assume that in developing countries (i.e., countries with lower economic status) firms compete for a smaller share of total potential adopters and, thus, potential early adopters. The more firms there are in the market, the more difficult it is for each firm to gain potential adopters and for the informational cascade to leave its fragile state. Thus, we propose the following:

H2: The negative effect of competition, where firms are more likely to reach takeoff when fewer competitors operate in the market, is stronger in countries with lower economic status.

3.4 Methodology

Modeling firm-level takeoff internationally requires **consideration of the clustered data structure** that is, firms are clustered in countries. Previous cross-national studies on category-level takeoff have not modeled the country market as a separate level of analysis. An advantage of our approach is that it captures the unobserved heterogeneity, and it is possible to assess the degree of within- and between-country variation.

We apply a **random coefficient discrete-time hazard model** (Barber et al. 2000). Such models have been applied in other disciplines, such as demography (Steele et al. 1996), education psychology (Petras et al. 2011), and behavioral research (Reardon et al. 2002). The discrete-time hazard refers to duration-model-like data in which the event (i.e., the firm-level takeoff) is measured in discrete time units (i.e., quarterly subscriber rates). The discrete-time hazard function is the conditional probability of an event occurring at time *t* for firm *i* in country *j*, given that the event has not occurred in previous time periods:

$$h_{ij}(t) = \Pr(y_{ij}(t) = 1 \mid y_{ij}(t-1) = 0) \tag{3.1}$$

Furthermore, we specifically **account for the duration dependence**. In a discrete-time model, which is most analogous to a parametric model using the exponential distribution, the hazard rate is flat with respect to time (i.e., it is a constant). If duration dependence is not taken into account, the estimates of the model will be consistent but inefficient and the standard errors will be incorrect. There are several options to address duration dependence, including correcting standard errors, including time dummies (Singer and Willet 1993, Van den Bulte and Iyengar 2011), using transformations on *t*, or smoothing functions such as Lowess and Cubic Splines (Beck et al. 1998).

We estimate a **logit that smooths time using cubic polynomial approximation** for the hazard to account for time dependency (Carter and Signorino 2010). Using cubic polynomials avoids estimation problems that occur when using time dummies (i.e., inefficiency and separation). Thus, we include t, t^2, and t^3 as regressors in the model, and we allow them to vary across countries (Reardon et al. 2002).[1]

The model includes **random effects for firms and countries**. In this model, we include time-invariant variables at both the firm and country level as well as time-varying covariates at the firm level. Thus, the model has the following form:

$$
\begin{aligned}
Y_{tij} &= \log\left(\frac{h_{tij}}{1-h_{tij}}\right) \\
&= \beta_{0_j} + \sum_{n=1}^{3} \beta_{n_j}(t)^n + \beta_{4_j} FV_{tij} + \beta_{5_j} FI^a_{ij} + \beta_{6_j} FI^b_{ij} + \beta_{7_j} FI^a_{ij} FI^b_{ij} + \beta_{8_j} FV_{tij} CI_j \\
\beta_{0_j} &= \gamma_{00} + \gamma_{01} CI_j + u_{0_j} \\
\beta_{n_j} &= \gamma_{n0} + u_{n_j} \\
\beta_{4_j} &= \gamma_{40} \\
\beta_{5_j} &= \gamma_{50} \\
\beta_{6_j} &= \gamma_{60} \\
\beta_{7_j} &= \gamma_{70} \\
\beta_{8_j} &= \gamma_{80}
\end{aligned}
\tag{3.2}
$$

whereby $u_{0_j} \sim N(0, \sigma^2_{u_0})$ and $u_{n_j} \sim N(0, \sigma^2_{u_n})$.

$\beta_{0_j} + \sum_{n=1}^{3} \beta_{n_j}(t)^n = \beta_{0_j} + \beta_{1j} t + \beta_{2j} t^2 + \beta_{3j} t^3$ is the **baseline hazard function** specified as a cubic polynomial approximation to the baseline hazard. It represents the function of time, which is called the logit of the baseline hazard function and captures changes in $h_{ij}(t)$. FV_{tij} is a firm-level time-varying covariate, FI^a_{ij} and FI^b_{ij} specify firm-level time-invariant variables, CI_j is a country-level time-invariant variable, $FI^a_{ij} FI^b_{ij}$ indicates an interaction between two firm-level time-invariant variables, and $FV_{tij} CI_j$ specifies a cross-level interaction between FV_{tij} and

[1] To avoid numerical instability resulting from large differences in magnitude between t^3 and other regressors (i.e., if the maximum duration is t = 26 resulting in a t that varies between 1^3 and 26^3), we will use $\frac{t}{100}$ and its square and cubed (Carter and Signorino 2010).

CI_j.[2]

We test the necessary **assumptions underlying discrete time hazard models**, i.e. linear additivity, proportionality, and no unobserved heterogeneity, by following standard procedures proposed by various authors (Harrell Jr. et al. 1996, Heckman and Singer 1984, Hess 1995, Singer and Willett 2003). In addition, to assess the quality of the model fit we examine the deviance residuals (Singer and Willett 2003).

3.5 Data

3.5.1 Description of data collection

This **study analyzes quarterly firm-level data** from the second quarter of 1996 to the third quarter of 2011 (62 time points) covering the product life of broadband Internet operators from their launch until today. The dataset includes the subscriber rates of 74.9% of all broadband Internet operators worldwide.[3] Due to its extensive scope, the data preparation process lasted two years.

We **collected subscriber figures from two commercial databases**. When comparing time series across the two sources and merging data series, we followed the procedures used in previous research (Tellis et al. 2003, Van Everdingen et al. 2009). We compared each time series of each broadband operator across the two sources and merged data series when the remainder of the time series was highly correlated or identical.

Some time series had **missing data**, especially shortly after service launch, potentially leading to problems determining whether the firm experienced takeoff. Following the approach of Chandrasekaran and Tellis (2008) and Van Everdingen et al. (2009), we collected

[2] Note that when estimating a random intercept model for binary response, the level-one variance is fixed at 3.29; this is due to the missing error term in the logit model (the residual variance is not estimated). Thus, errors are assumed to follow a Bernoulli distribution with an unknown residual variance of π2/3=3.29.

[3] There were 523,070,000 broadband Internet subscribers worldwide in 2010 (Vanier 2011). In our data, we observe 391,796,387 broadband Internet subscribers in 2010 (i.e., 74.90% of all broadband Internet subscribers).

missing information from external sources, such as company homepages and reports. Subsequently, 17 firms had to be excluded from the analysis due to too many missing values.

The data also included **regional broadband Internet operators** that only operate in some areas of the country (e.g., Alaska Communications in the United States). We identified 78 regional operators across 17 countries by external search, mainly through the companies' webpage profiles. Because thresholds for firm-level takeoff are determined based on the penetration of households in the whole country (Tellis et al. 2003), dealing with regional operators is problematic. Because such firms would have falsely been indicated as having no firm-level takeoff, regional operators were excluded from the analysis. The final dataset consists of quarterly subscriber figures for 428 operators in 81 countries.

Table 3.1 provides an **overview of the variables and their measurements** included in the discrete-time hazard model. A detailed discussion is presented in the following section. The correlation matrix, descriptive statistics on the time-to-takeoff, as well as further descriptives on the occurrence of firm-level takeoff in relation to category-level takeoff can be found in Appendix 3.1, Appendix 3.2, and Appendix 3.3 respectively.

Table 3.1: Overview of variables and their measurement in the model

Variable	Measurement
Dependent variable	
Occurrence of firm-level takeoff	Binary variable indicating the quarter in which an operator reached firm-level takeoff
Independent Variables	
Firm-level time-invariant	
Entry in relation to category-level takeoff - Entry at category-level takeoff - Entry after category-level takeoff	Two binary variables indicating a firm's decision to enter the market at or after category-level takeoff; the reference category is entering before category-level takeoff
Time difference in firm entry to category-level takeoff	Count variable that counts the absolute distance to category-level takeoff in quarters
Entry after category-level takeoff × time difference in firm entry to category-level takeoff	Interaction effect between entry after category-level takeoff and time-difference in a firm's entry to category-level takeoff

Table 3.1 (continued)

Firm-level time-varying	
Number of competitors	Count variable of the number of competitors in the country market in a specific quarter
Country-level time-invariant	
Economic state of the country - High income - Upper middle income	Two binary variables for countries with high income and upper middle income; the reference category is lower middle income
Cross-level interactions	
Number of competitors × economic state of the country - Competitors × high income - Competitors × upper middle income	Two interactions between the number of competitors and the country's developmental stage
Control variables	
Firm-level time-invariant	
First mover	Binary variable indicating whether the operator was the first to enter the market
Early followers	Binary variable indicating early followers, i.e. firms entering the year after service launch
Order-of-entry	Count variable that indicates the order of entry
Technology - DSL - Cable	Binary variables indicating whether the firm operates DSL or cable technology; the reference category is all other technologies
Incumbent operator	Binary variable indicating the incumbent operator in a country
Growth in GDP	Percentage growth in country GDP from (t-1) to t
Country-level time-invariant	
Population density	Population density per square kilometer in a country (mean for 1995, 2000, 2005, and 2010)

3.5.2 Operationalization of the dependent variable

Firm-level takeoff is a binary variable that also acts as a censoring indicator: "1" indicates a takeoff in the respective quarter, whereas "0" indicates right censoring of the firm (i.e., the event does not occur in the observed time periods).

To determine firm-level takeoff, we adopt the **approach proposed by Tellis et al. (2003)**. To apply their threshold rule, we use the growth in a firm's market penetration in the same way they use the growth in market penetration of a product category in a country. To calculate the market penetration, we divide the subscriber figures by the country-specific household statistics for each quarter.[4]

We performed **several steps to determine the thresholds for firm-level takeoff**. First, we applied the same thresholds as Tellis et al. (2003). Independently, we asked marketing scholars to determine the firm-level takeoff based on the data. We found a match between both approaches for a large number of firms. However, there were some discrepancies that could not be ignored. Thus, we decided to reassess the thresholds in a second step. We conducted additional interviews with industry experts as well as leading academics in the field. We adapted the thresholds to our context and found that 190 out of 428 Internet broadband operators experienced takeoff. 238 operators do not experience takeoff in subscriber rates within the observed period and were thus considered censored observations. A graphical visualization of the thresholds applied by Tellis et al. (2003) compared to the thresholds used in this study can be found in Appendix 3.4.

Care must be taken when defining the thresholds (i.e., the market penetration in t and the required growth rate of the market penetration in t+1 to observe firm-level takeoff in t). As market penetration increases, the required threshold to signal firm-level takeoff decreases (Tellis et al. 2003). For any level of a firm's market penetration, a threshold is defined to signal firm-level takeoff. This threshold is based on the change of the market penetration from t to t+1 (e.g., at a market penetration in t of 0.5% the growth rate must be at least 300%; i.e., the market penetration in t+1 must be at least 2%). For a different market penetration in t, the threshold to signal takeoff is also different (e.g., at a market penetration in t of 0.6%, the growth rate must be at least 250%; i.e., the market penetration in t+1 must be at least 2.1%).

To **ensure that the threshold rule does not become inconsistent**, the thresholds must be defined such that the required market penetration in t+1 increases monotonically. This re-

[4] We used the annual household statistics from 1996 to 2011 for all countries in the study (Euromonitor 2012). We calculated quarterly household sizes by applying cubic spline interpolation.

quirement is violated if at a certain market penetration in t, the threshold to signal takeoff leads to a market penetration in t+1 that is smaller than for the preceding cases (e.g., in the aforementioned case of a marketing penetration in t of 0.6%, a growth rate of 200% would lead to a market penetration in t+1 of 1.8%; this is less than 2%, which was the minimal market penetration in t+1 required at 0.5%).

3.5.3 Operationalization of the independent variables

We **operationalize a firm's strategic decision to enter before, at, or after category-level takeoff** by including two dummies as time-invariant binary variables. The reference category is firms entering before category-level takeoff. The thresholds for firm-level takeoff are applied to determine the takeoffs at the category level. Visual inspection of the category-level takeoffs clearly justifies this approach. We find that the category-level takeoff of broadband Internet services is reached in 75 of the 81 countries.[5]

We also consider the **time between a firm's market entry and the category-level takeoff** (Markovitch and Golder 2008). This variable is centered at two quarters (Aiken and West 1991). By including an interaction between this covariate and the variable indicating a firm's market entry after category-level takeoff, we are able to model whether the impact of a firm's decision to enter before or after category-level takeoff on the probability of reaching firm-level takeoff varies with increasing distance to category-level takeoff.

We consider the **number of competitors** (Fischer et al. 2010) as a time-varying firm-level covariate. This covariate indicates the number of broadband operators during each quarter in each country and is centered at two competitors (Aiken and West 1991).

As a country-level covariate, we include dummy variables that allow us to distinguish between **countries with different economic statuses** (World Bank 2011), i.e., high income, upper middle income and lower middle income countries (see Table 3.2). Dummies are in-

[5] The six countries where no category takeoff is observed are Albania, Bolivia, Nicaragua, Pakistan, Syrian Arab Republic, and Yemen.

cluded for the first two groups. Thus, the lower middle income group is the reference category. Countries from the low income category are not part of our dataset.

Table 3.2: Definition of income groups

Income group	GNI per capita thresholds for income groups	Countries included in the present study
High income	$12,476 or more	Australia, Austria, Bahrain, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, Ireland, Italy, Japan, South Korea, Latvia, Liechtenstein, Luxembourg, Netherlands, New Zealand, Malta, Monaco, New Caledonia, Nicaragua, Norway, Oman, Poland, Portugal, Qatar, Saudi Arabia, Singapore, Slovak Republic, Spain, Sweden, Switzerland, United Kingdom, United States
Upper middle income	$4,036 - $12,475	Albania, Algeria, Argentina, Belarus, Brazil, Bulgaria, Chile, Colombia, Jamaica, Lithuania, Macedonia, Mauritius, Mexico, Montenegro, Panama, Peru, Romania, Russia, South Africa, Suriname, Turkey, Uruguay, Venezuela
Lower middle income	$1,026 - $4,035	Bolivia, China, Egypt, India, Indonesia, Moldova, Morocco, Pakistan, Philippines, Senegal, Sri Lanka, Syrian Arab Republic, Thailand, Tunisia, Ukraine, Vietnam, Yemen
Low income	$1,025 or less	(no data available)

Note: Definition according to (World Bank 2011).

We create **cross-level interaction terms** (Aguinis et al. 2013) between the number of competitors and the two dummy variables indicating the economic status of the country. Thus, we consider that the effect of competition may differ for high and upper middle income countries compared with lower middle income countries. Hauser et al. (2006) highlighted the increasing interest in interaction effects rather than simply the main effect of research on innovation.

3.5.4 Operationalization of the control variables

The **first mover** is the first broadband Internet operator to enter a country market. If several operators in the same country start their offering in the same quarter, they are all referred to as the first mover. This is the case in four countries (Canada, Columbia, South Korea, and

Lithuania). This approach is in line with previous literature on the pioneer advantage (for an overview of pioneer definitions, see Golder and Tellis 1993).

Early followers are defined as the firm(s) entering the country the year after the first mover (Min et al. 2006, Wang et al. 2010). Several studies address the question of whether pioneer and early followers have an advantage in penetrating the market (e.g., Golder and Tellis 1993, Lilien and Yoon 1990, Narasimhan and Zhang 2000).

As a firm-level control variable, we account for the **order of market entry** (Fischer et al. 2010). If multiple firms enter in the same quarter, they are assigned the same rank. Contrary to first mover and early follower variables, the order of market entry does not consider the time between the initial launch of operations of each firm.

We also account for the **technology** of the operator. We therefore distinguish among the technologies DSL, cable, and other (i.e., all forms of fiber, wireless and satellite technologies).

Moreover, we consider whether the operator is the **incumbent operator** in a country market. Incumbent operators are regional monopoly firms providing telecom services prior to the introduction of competition. Again, we use company homepages and reports to determine the respective status of the operator. Overall, 92 firms in 80 countries are categorized as incumbents.[6] Thus, we control for presumably dominant firms (e.g., Bayus et al. 2007).

Further, **growth in the gross domestic product (GDP)** is included as a firm-level time-varying measure for economic development (United Nations 2010). The economic wealth of a country affects the demand and affordability of new products and, thus, firm-level takeoff (Tellis et al. 2003, Van Everdingen et al. 2009). The variable must be modeled at the firm-level because the hazard model accounts for the time since market entry, not the actual quar-

[6] In eight countries (Brazil, China, Colombia, Hungary, India, Japan, South Korea, and United States), two incumbents are present. In case of Canada and Finland, three incumbents were observed. For Russia, the incumbent operator is a regional operator (Moscow Telecom) which thus has been previously excluded from the dataset.

ters. Therefore, it is different for firms *i* in the same country *j* at the same time point *t*.

Finally, we account for **population density** as a country-level control variable (United Nations 2010). Easier communication and information transfer in countries with higher population densities results in a higher probability of product adoption and, thus, firm-level takeoff (Van Everdingen et al. 2009).

3.6 Results

3.6.1 Evaluation of the modeling approach

Whether the estimation of a random coefficient model is necessary for our data can be evaluated by **comparing the single-level to the two-level null model**. The log-likelihood comparison test indicates a difference in log-likelihoods of - 23.00 (df = 1).

Furthermore, the corresponding **inter-class correlation** (ICC, also known as variance partitioning coefficient) can be used for a detailed assessment of the variance explained by each level. We calculate the logistic ICC whereby the level-one variance is fixed at 3.29. Based on the intercept-only two-level model, we estimate the corresponding ICC as follows:

$$\text{Logistic-ICC} = \frac{\mathrm{Var}(u_{0j})}{\mathrm{Var}(u_{0j}) + 3.29} = 0.2257 \tag{3.3}$$

Thus, 22.57 % of the residual variation is explained by level two (i.e., common to firms of the same country). The results support the choice of a random coefficient model.

We present a **series of four models** (see Table 3.3 and Table 3.4) to account for the presence of interaction effects. First, a main-effect-only model is estimated. In the following, we run two models adding each interaction effect separately. Finally, the full model, including all hypothesized effects, is estimated. The results indicate that the latter model fits the data best.

Next, we **examine temporal dependence**. The time effect t is positive and significant (b = 3.08, p < 0.01), whereas the squared and cubed terms are not significant. In consequence, we observe temporal dependence in our model, indicated by a linear positive effect. Thus, the baseline hazard increases linearly with respect to time. In other words, the probability of observing takeoff increases linearly the longer a firm operates in a country market.

Table 3.3: Results of the random-coefficient discrete time hazard models

	Main effects only					Interaction 1				
	Est.	SE	z-value	Pr (>|z|)	Sig.	Est.	SE	z-value	Pr (>|z|)	Sig.
Fixed effects:										
(Intercept)	-6.57	0.67	-9.76	0.00	***	-5.93	0.68	-8.76	0.00	***
Entry at category-level takeoff	0.69	0.36	1.94	0.05	.	0.31	0.37	0.84	0.40	ns
Entry after category-level takeoff	0.31	0.27	1.15	0.25	ns	0.04	0.29	0.15	0.88	ns
Time difference in entry to category-level takeoff	-0.02	0.02	-0.95	0.34	ns	-0.12	0.03	-3.83	0.00	***
Entry after cat.-level takeoff × dist. entry to cat.-level takeoff						0.16	0.04	4.33	0.00	***
Number of competitors	-0.05	0.02	-2.45	0.01	*	-0.05	0.02	-1.94	0.05	.
Economy: high income	1.84	0.36	5.10	0.00	***	1.55	0.37	4.17	0.00	***
Economy: midup income	1.04	0.38	2.73	0.01	**	0.76	0.39	1.93	0.05	.
Economy: high income × number of competitors										
Economy: midup income × number of competitors										
Control variables:										
First mover	0.45	0.32	1.38	0.17	ns	0.64	0.33	1.93	0.05	.
Early followers	0.32	0.28	1.13	0.26	ns	0.29	0.28	1.03	0.31	ns
Market entry order	-0.04	0.06	-0.72	0.47	ns	-0.16	0.06	-2.52	0.01	*
Technology: DSL	0.35	0.27	1.29	0.20	ns	0.44	0.28	1.61	0.11	ns
Technology: cable	-0.78	0.30	-2.58	0.01	**	-0.68	0.30	-2.26	0.02	*
Incumbent operator	0.97	0.24	4.03	0.00	***	1.08	0.25	4.38	0.00	***
GDP growth	0.22	0.11	2.02	0.04	*	0.22	0.11	2.10	0.04	*
Population density	0.24	0.11	2.13	0.03	*	0.20	0.10	2.01	0.04	*
t	3.00	1.15	2.62	0.01	**	2.96	1.16	2.54	0.01	*
t^2	-1.79	1.04	-1.73	0.08	.	-1.61	1.06	-1.53	0.13	ns
t^3	0.32	0.27	1.19	0.23	ns	0.26	0.28	0.94	0.35	ns
Random effects:	**Est.**	**STD**				**Est.**	**STD**			
Country cluster	1.56	1.25				1.33	1.15			
t	0.88	0.94				1.57	1.25			
t^2	0.00	0.05				0.12	0.34			
t^3	0.01	0.07				0.01	0.07			
Model fit:										
AIC		1525					1507			
BIC		1715					1705			
Log Likelihood		-734.5					-724.7			
Deviance		1469					1449			

Note: *** = 0.001, ** = 0.01, * = 0.05, **.** = .1; Est. = unstandardized estimates, SE = standard error, STD = standard deviation, Sig. = significance, ns = not significant.

Table 3.4: Results of the random-coefficient discrete time hazard models (continued)

	Interaction 2					Full model				
	Est.	SE	z-value	Pr (>|z|)	Sig.	Est.	SE	z-value	Pr (>|z|)	Sig.
Fixed effects:										
(Intercept)	-6.11	0.71	-8.57	0.00	***	-5.07	0.72	-7.06	0.00	***
Entry at category-level takeoff	0.72	0.36	1.98	0.05	*	0.25	0.37	0.67	0.50	ns
Entry after category-level takeoff	0.32	0.28	1.15	0.25	ns	0.01	0.29	0.03	0.98	ns
Time difference in entry to category-level takeoff	-0.02	0.02	-1.24	0.21	ns	-0.14	0.03	-4.50	0.00	***
Entry after cat.-level takeoff × dist. entry to cat.-level takeoff						0.19	0.04	4.93	0.00	***
Number of competitors	-0.24	0.10	-2.31	0.02	*	-0.35	0.11	-3.17	0.00	**
Economy: high income	1.43	0.42	3.38	0.00	***	0.71	0.44	1.62	0.11	ns
Economy: midup income	0.67	0.45	1.49	0.14	ns	-0.06	0.47	-0.13	0.90	ns
Economy: high income × number of competitors	0.19	0.10	1.85	0.06	.	0.32	0.11	2.85	0.00	**
Economy: midup income × number of competitors	0.18	0.11	1.69	0.09	.	0.31	0.12	2.67	0.01	**
Control variables:										
First mover	0.37	0.33	1.12	0.26	ns	0.57	0.34	1.68	0.09	.
Early followers	0.29	0.28	1.02	0.31	ns	0.28	0.28	0.98	0.33	
Market entry order	-0.05	0.06	-0.78	0.44	ns	-0.18	0.06	-2.79	0.01	**
Technology: DSL	0.30	0.28	1.06	0.29	ns	0.38	0.28	1.36	0.17	ns
Technology: cable	-0.84	0.31	-2.73	0.01	**	-0.73	0.30	-2.41	0.02	*
Incumbent operator	0.95	0.25	3.86	0.00	***	1.09	0.25	4.30	0.00	***
GDP growth	0.25	0.11	2.24	0.03	*	0.27	0.11	2.46	0.01	*
Population density	0.25	0.11	2.22	0.03	*	0.22	0.10	2.16	0.03	*
t	2.99	1.16	2.57	0.01	*	3.08	1.18	2.61	0.01	**
t^2	-1.75	1.06	-1.66	0.10	.	-1.65	1.07	-1.54	0.12	ns
t^3	0.30	0.28	1.10	0.27	ns	0.26	0.28	0.93	0.35	ns
Random effects:	**Est.**	**STD**				**Est.**	**STD**			
Country cluster (Intercept)	1.56	1.25				1.49	1.22			
t	1.13	1.06				2.71	1.64			
t^2	0.01	0.10				0.52	0.72			
t^3	0.00	0.06				0.03	0.16			
Model fit:										
AIC		1525					1502			
BIC		1729					1712			
Log Likelihood		-732.6					-719.8			
Deviance		1465					1440			

Note: *** = 0.001, ** = 0.01, * = 0.05, **.** = .1; Est. = unstandardized estimates, SE = standard error, STD = standard deviation, Sig. = significance, ns = not significant.

3.6.2 Relationship between firm- and category-level takeoff

The **distribution of takeoffs** for firms entering before or after category-level takeoff yields initial insights into the relationship between firm- and category-level takeoff (see Table 3.5). For firms entering before category-level takeoff, the average time to takeoff is 12.5 quarters (median: 10). This duration is much shorter for firms entering after category-level takeoff (7.67 quarters; median: 5). All firm-level takeoffs occur at or after category-level takeoff. We examine those firms entering after category-level takeoff that do not demonstrate firm-level takeoff to ensure that the firms in our data operate long enough to potentially reach firm-level takeoff. Only one firm is observed that is present in the market for less than the average time to firm-level takeoff of 7.36 quarters.

Table 3.5: Firm-level takeoff depending on timing of market entry

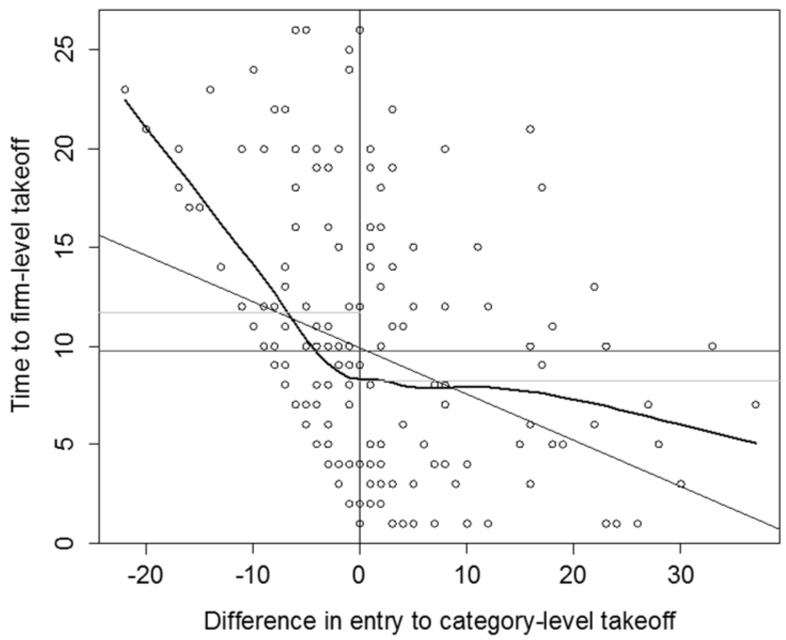
	Firm-level takeoff		
	Number of firms	**Time in quarters (mean)**	**Time in quarters (median)**
Market entry before category-level takeoff	98	12.5	10
Market entry at or after time of category-level takeoff	92	7.67	5

In **H1.1**, we hypothesized that firms would be more likely to reach firm-level takeoff when entering after category-level takeoff. The results of the full model provide support for this hypothesis. Although there is a negative effect ($- 0.14 \times x_{\text{time-difference}} \leq - 0.14$) for all firms that have entered a market before category-level takeoff regardless of the time difference in entry to category-level takeoff ($x_{\text{time-difference}}$), this effect is positive if the firm entered after category-level takeoff ($- 0.14 \times x_{\text{time-difference}} + 0.19 \times 1 \times x_{\text{time-difference}} \geq 0.05$).[7] The probability of reaching firm-level takeoff is larger after category-level takeoff. In other words, a firm entering after category-level takeoff needs less time to reach takeoff than firms that enter before category-level takeoff.

As hypothesized in **H1.2a and H1.2b**, we now take a closer look at the hypothesized effects concerning the time difference in market entry to category-level takeoff on firm-level takeoff. Figure 3.2 plots the time to firm-level takeoff against the time difference in market entry to category-level takeoff. The time to takeoff decreases sharply upon entering at category-level takeoff and then slowly flattens.

[7] Note that the main effect of "entry after category-level takeoff" is not significant and thus, is not considered in the equations above.

Figure 3.2: Time to firm-level takeoff and difference in entry to category-level takeoff



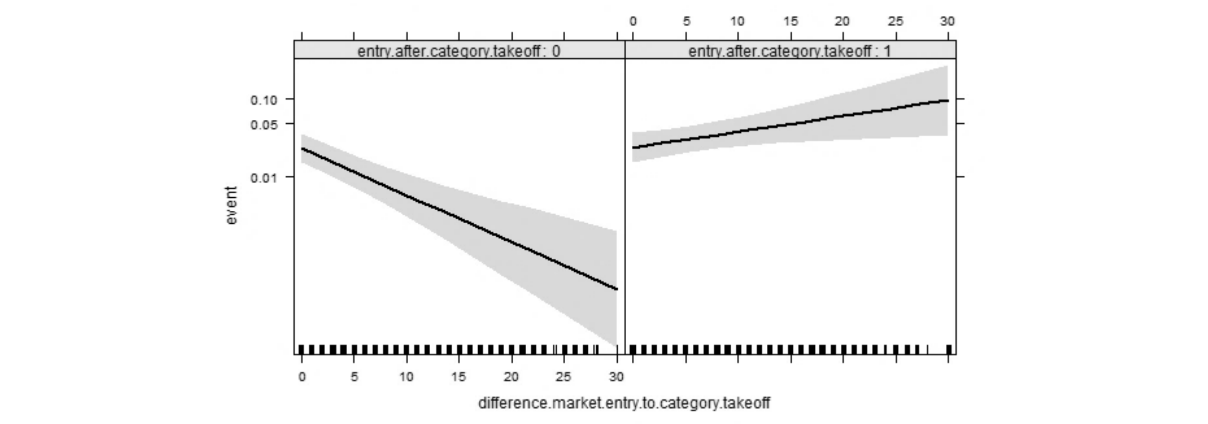
Note: The vertical line at zero indicates the time of category-level takeoff; the middle horizontal line indicates the mean time-to-takeoff; the upper gray horizontal line indicates the mean time to takeoff for firms entering before category-level takeoff. The lower gray horizontal line indicates the mean time to takeoff for firms entering after category-level takeoff. The thick curve indicates the loess smoothed function of the time to firm-level takeoff. The straight line with the negative slope indicates the linear trend.

In **H1.2a**, we hypothesized that for firms entering before category-level takeoff, the probability of firm-level takeoff increases the closer the market entry is to the category-level takeoff. The significant negative effect of time difference in entry to category-level takeoff ($b = -0.14$, $p < 0.001$) indicates the effect for firms entering before category-level takeoff (the reference group) and thus supports this hypothesis.

In **H1.2b**, we hypothesized that for firms entering after category-level takeoff, the probability of firm-level takeoff decreases the greater the time difference is between a firm's entry and the category-level takeoff. However, the model indicates a positive, though rather small, interaction effect ($- 0.14 \times x_{\text{time-difference}} + 0.19 \times 1 \times x_{\text{time-difference}} \geq 0.05$). Thus, we reject this hypothesis.

The **effect is illustrated in the plot** shown in Figure 3.3. On the left side, it is clear that for firms entering before category-level takeoff, the likelihood of observing firm-level takeoff (the event) decreases with distance to category-level takeoff, whereas the opposite is found for firms entering after category-level takeoff (right side).

Figure 3.3: Effect plot for the effect of entry at or after category-level takeoff



3.6.3 Relationships among firm's competition, country's economic state and firm-level takeoff

An **initial understanding of the varying influence of competition across countries** leads to Table 3.6, which illustrates the average time to firm-level takeoff according to the economic state of the country and the number of competitors at the time of firm-level takeoff. For all income groups, a consistent pattern in the mean (and median) number of competitors can be observed. Firm-level time to takeoff is shorter when fewer competitors are in the market (compared by column). The difference between a low and high number of competitors (compared by row) is comparably low for firms operating in upper middle income countries, whereas it is greater in high income countries and is greater in lower middle income countries. This result indicates that the effect of competition is stronger in lower middle income countries compared with the other income groups. This result becomes clear when considering the median time to firm-level takeoff.

Table 3.6: Descriptives on income group and number of competitors

Income group	Low number of competitors		High number of competitors	
	Mean	Median	Mean	Median
High income (140 firms)	6.78 (74 firms)	6	11.65 (66 firms)	11
Upper middle income (36 firms)	10.5 (20 firms)	10.5	13.44 (16 firms)	13
Lower middle income (12 firms)	12.86 (7 firms)	9	20.71 (7 firms)	20

Note: Samples contain firms that reach takeoff (190 firms); observations are split at the median number of competitors: median=6 for high income, median=4 for upper middle income, median=1.5 for lower middle income.

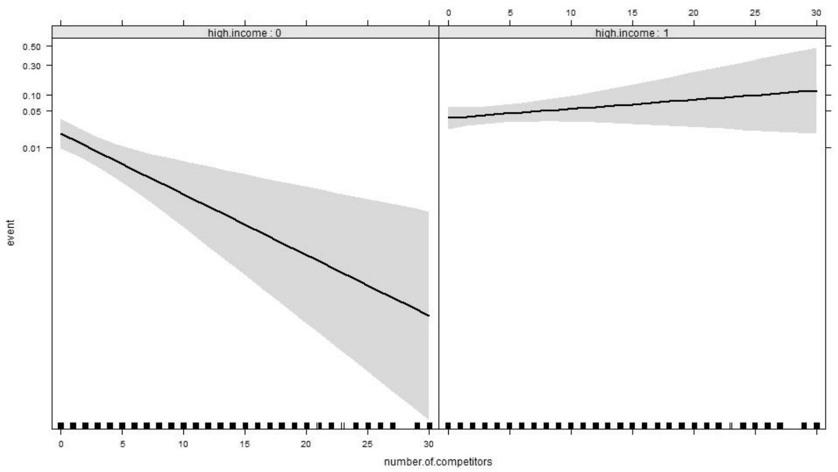
In **H2**, we hypothesized a stronger negative effect of competition in countries with lower economic status compared with countries with higher economic status. When examining the results from the full model, the cross-level interactions between the economic status of the country and the number of competitors provide support for this hypothesis. The main effect for the number of competitors is significantly negative ($b = -0.35$, $p < 0.01$), whereas the main effects for the economic status of the country are not significant. We find significant positive effects for both interactions ($b = 0.32$, $p < 0.01$; $b = 0.31$, $p < 0.01$). The positive interaction terms indicate that there is an additional effect that is not explained by the number of competitors and economic status of a country alone. Both indicate a stronger effect of competition in high- or upper middle income countries compared with the reference category of lower middle income countries. The negative effect of competition (i.e., the probability of takeoff raises when fewer competitors are present in the market) is stronger for the lower middle income countries ($- 0.35 \times x_{competition}$, $p < 0.01$) than for the upper middle ($- 0.35 \times x_{competition} + 0.31 \times 1 \times x_{competition} \leq - 0.04$) and high income countries ($- 0.35 \times x_{competition} + 0.32 \times 1 \times x_{competition} \leq - 0.03$).[8] In other words, for firms in the high and upper middle income countries competition has a significantly different impact on the probability of firm-level takeoff than for firms in lower middle income countries.

[8] The main effects of both income variables are not significant.

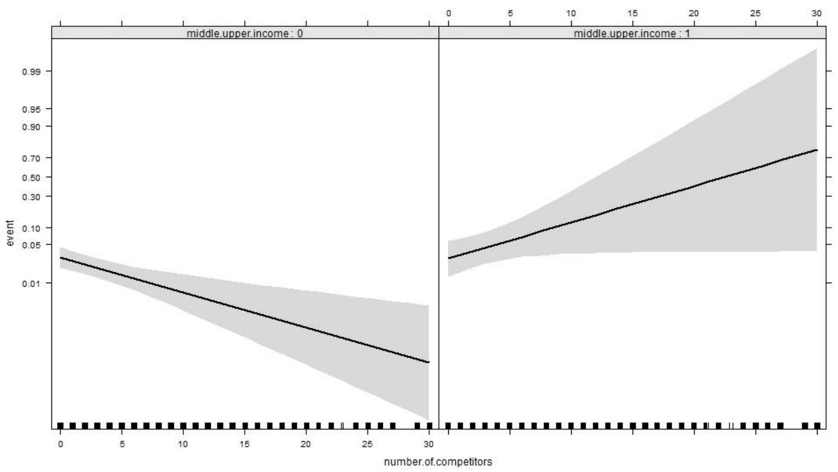
The **effect plots for the interactions** of economic status and number of competitors on the time to takeoff in provide a visual illustration (see Figure 3.4). The plots indicate a slightly positive effect for high and upper middle income countries, demonstrating that the negative competition effect is less strong (i.e., outweighed by the positive main effects of high and middle upper income).

Figure 3.4: Effect plots for the effect of number of competitors

A - High income × number of competitors



B - Upper middle income × number of competitors



3.6.4 Effects of control variables

We include several **control variables** in the model. At the firm level, we find a positive, marginally significant effect for the first mover ($b = 0.57$, $p < 0.1$). The effect indicates that a firm that enters the market as a pioneer is more likely to reach firm-level takeoff than firms that follow. The effect of market entry order is negatively significant ($b = - 0.18$, $p < 0.01$), indicating that the probability of takeoff is higher the earlier a firm enters the market. Furthermore, we find a significant effect for cable operators ($b = - 0.73$, $p < 0.05$). The negative effect indicates that cable operators have a lower probability of reaching firm-level takeoff. Finally, the effect of being the incumbent operator is positively significant ($b = 1.09$, $p < 0.001$), indicating that the likelihood of firm-level takeoff is high for the incumbent operator. The effects of early followers and DSL operators are not significant. At the country level, we find positive effects of population density ($b = 0.22$, $p < 0.05$) and growth in GDP ($b = 0.27$, $p < 0.05$). Firms operating in countries with a higher population density and higher growth in GDP are more likely to reach firm-level takeoff than firms in countries where both are lower.

3.7 Discussion

3.7.1 Implications

Our study has **multiple important implications for practitioners and academics**. One finding deserves particular attention: firm-level takeoff, the concept we introduced in this study, allows a more precise estimate of how long a firm requires to be successful. At the same time, the use of firm-level takeoff as a success measure allows appropriate modeling of country- and firm-level contexts. Based on our initial research questions we are able to confirm the impact of category-level takeoff, a firm's competition and a country's economic status on firm-level takeoff. We discuss the implications in the following sections.

With regards to the relationship between firm- and category-level takeoff, the results show that the probability of reaching firm-level takeoff increases when the firm enters after category-level takeoff. Examining in detail the firms that enter before and after category-level takeoff, we find the following: (1) The negative effect of entering the market early decreases if little time passes between market-entry and category-level takeoff. (2) The decrease in time to reach firm-level takeoff for firms entering after category-level takeoff is rather negligible. Practitioners should pay attention to the relationship between firm-level takeoff and category-level takeoff for two operational reasons: optimizing (1) market entry timing and (2) resource allocation.

First, **a firm must assess whether it is worthwhile to enter a market**. Determining whether category-level takeoff has occurred or how much time has passed since category-level takeoff may provide important information to determine the right timing for market entry. The right market entry timing, in turn, influences the likelihood that a firm's offering in a particular category will take off. Both scenarios, entering before and entering after category-level takeoff, should be evaluated by decision makers. Information on category-level takeoff allows a more precise estimation of the time to firm-level takeoff, which is important in preparing a realistic business case. This information can optimize resource planning, and early dropouts of the market can eventually be decreased. Firms can consider whether to enter early or wait until the product category has proven successful in the market. Furthermore, firms can learn from the experience of others that entered the market earlier, allowing later entrants to make use of that experience and affecting their firms' success (Greve and Taylor 2000).

It is important to **view the results within the context of the wide body of literature on first mover and early follower advantages** (e.g., Chen and Xie 2007, Karakaya and Stahl 1989, Prins and Verhoef 2007). The results of our model confirm a positive effect for the first mover but a non-significant effect for early followers. Including these effects in the model enables us to compare the relevance of this metric to the newly introduced metric of the exact timing of market entry in relation to category-level takeoff. Table 3.7 shows the mean times to takeoff for first movers and early followers illustrating that firms entering shortly before category-level takeoff reach firm-level takeoff faster than those that enter much earlier.

Table 3.7: Time to firm-level takeoff for first mover and early follower

Difference in entry to category-level takeoff: median split	Time until firm-level takeoff
First mover (54 of 86 first movers observe firm-level takeoff)	
Entry earlier than 6 quarters before category-level takeoff	13.85 (27 firms)
Entry 0 to 6 quarters before category-level takeoff	5.59 (27 firms)
Early follower (39 of 59 early followers observe firm-level takeoff)	
Entry earlier than 3 quarters before category-level takeoff	15.53.0 (17 firms)
Entry later than 3 quarters before category-level takeoff	8.95 (22 firms)
- Entry before category-level takeoff	7.17 (6 firms)
- Entry after category-level takeoff	9.62 (16 firms)

Note: Early followers are, per definition, firms entering the year after the first mover. Thus, we observe several early followers entering after the category-level takeoff.

For example, the results indicate that the **first mover advantage decreases** behind the effect of distance in entry to category-level takeoff after approximately four quarters ($0.57 \times x_{\text{first-mover}} + (-0.14) \times x_{\text{time-difference}} \leq 0$ for $x_{\text{time-difference}} \geq 4.07$). For a first mover entering earlier than four quarters before category-level takeoff, the negative effect is stronger (i.e., the equation becomes negative). Thus, being the first in a market and considering whether the product category takes off in a reasonable time after the initial launch of a new product are factors relevant for success.

Second, for **firms operating in a market where category-level takeoff has not yet occurred**, the relationship between category- and firm-level takeoff is important to optimize resource allocation. Practitioners should continuously monitor the occurrence of category-level takeoff and adapt their forecasts according to the market situation. Once category-level takeoff occurs, it increases the probability of firm-level takeoff and has decisive consequences for a firm's operations management. The occurrence of category-level takeoff allows a better prediction of firm-level takeoff, which, by definition, accompanies a rapid increase in demand. Being able to satisfy this demand while avoiding the negative consequences of not doing so requires significant adaptation in resource allocation over a certain period before firm-level takeoff. Thus, the ability to precisely predict firm-level takeoff far ahead of its occurrence allows for efficient resource planning.

Regarding the relationship among firm's competition, country's economic state, and firm-level takeoff, our findings provide initial evidence that firm-level time to takeoff takes longer in countries with lower income status. Further, the results show that the effect of firms' greater likelihood of reaching takeoff when only a few competitors are present in the market is stronger in those countries. The results also indicate that this effect is negligible in countries with higher income.

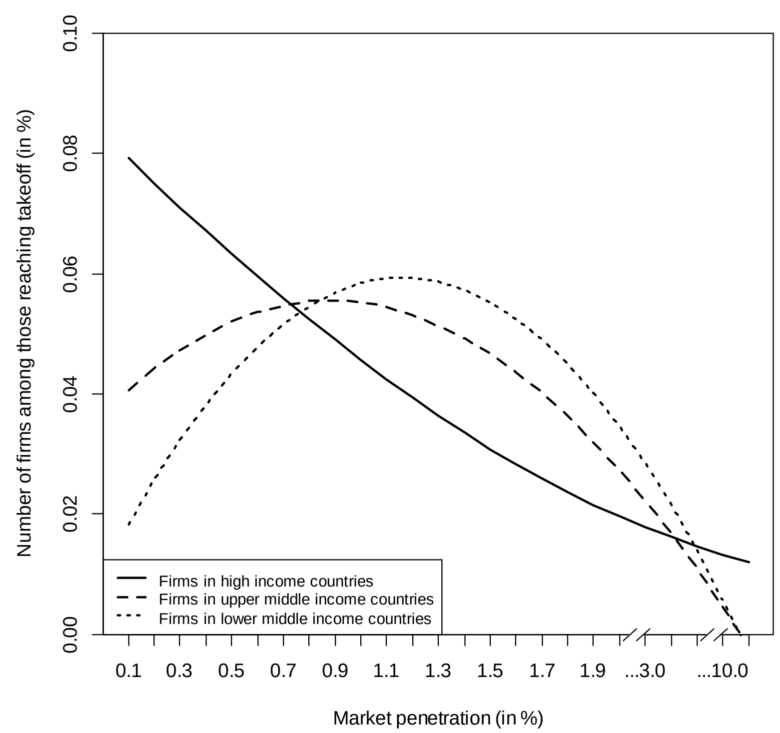
Developing countries are increasingly becoming economically important for a variety of reasons. Due to the limited remaining potential in developed countries (Peres et al. 2010) and the enormous future potential in emerging and developing markets, firms from developed countries seek to expand into those markets. It is crucial for both managers and researchers to develop an understanding of the fundamental differences between developed and developing countries and the impact of those differences on the success of launching new products.

Practitioners can use the results of our study in two ways: (1) Before making a market entry decision, practitioners should consider the country-specific variation in the time until a firm's product takes off by examining the average critical market penetration to reach firm-level takeoff. (2) If a firm has already entered a developing country, it should use the findings to continuously adapt its forecasts, market strategy, and resource planning according to its actual competitive situation.

The **critical market penetration rate** to gain momentum for a new offer may differ across countries with different economic states. We can calculate the critical market penetration at which a firm's products, on average, reach takeoff in different country markets (see Figure 3.5). In addition to providing a more accurate forecast to optimize a firm's operations, this metric can be used for more reliable communication with investors.

Calculating the critical market penetration leads to the following results. Most firms in high income countries reach takeoff at a lower penetration level (approx. 0.1%) than upper middle income (approx. 0.9%) and lower middle income (approx. 1.2%) countries. The lower penetration levels in high income countries can be explained by their denser network structures and faster information spread. Thus, growth gains greater momentum, and the thresholds for reaching firm-level takeoff are met sooner. Firms in lower income countries need a larger customer base to be successful in the market. Attracting customers, adapting the product to the country's context, and reaching the critical number of customers are more difficult than in other countries. A firm must address limited purchasing power to develop strategies for the very poor (Warnholz 2008) and must emphasize customer education. In the case of broadband Internet, this means providing low-cost devices and terminals for broadband Internet use and promoting digital literacy (Kim et al. 2010). Firms considering extending their business to developing countries may need patience paired with innovative strategies.

Figure 3.5: Critical market penetration for countries with different economic states



Note: The curves indicate the loess smoothed functions of the market penetration and the number of firms, which reach firm-level takeoff at each penetration level (as percentage of all firms reaching firm-level takeoff).

If a **firm has already entered a developing country**, it must consider the competitive setting and adapt its decisions concerning entry barriers, commitment of resources, and length of stay in a market accordingly. First, by being aware of the negative consequences of intense competition in developing countries, a firm can decide to establish entry barriers (e.g., Han et al. 2001). The relative importance of competition in developing countries may be due to a situation in which the market potential is not yet on par with developed countries. Consequently, the number of early adopters is likely to be smaller than in comparable developed countries, making it more difficult to attract consumers when facing multiple competitors. Second, when faced with new entrants, a firm must adapt its forecasts to guarantee efficient resource allocation. Our results provide broad guidelines for the longer amount of time to firm-level takeoff in cases of an increasing number of competitors, thus, enabling practitioners to adapt resource planning accordingly. Eventually, this information may lead to the decision to exit the market if reaching firm-level takeoff becomes an unrealistic endeavor.

3.7.2 Limitations and further research

Certain **limitations of our research may provide an agenda for future research**. First, a worthwhile path would be to enhance our analysis by including data (1) on multiple industries, (2) on multiple products of one firm, and (3) over a longer time span. Our study focuses on the aggregated product portfolio of one firm in one industry. Although it is a challenging and time-intensive task to gather this type of data on a cross-national basis, this approach may allow others to analyze in detail effects such as how firm-level takeoff varies between industries across countries or how the success of one product influences the success of a firm's product portfolio. Increasing the time horizon would enable the simultaneous analysis of further characteristic events of a product's life cycle, such as its peak sales and slowdown (Fischer et al. 2010, Golder and Tellis 2004).

Furthermore, **future research should consider analyzing country- and firm-level variables** that might be of specific interest in explaining firm-level takeoff. At the firm level, marketing variables such as price or advertising spending seem to be of specific interest (Chandrasekaran et al. 2013, Golder and Tellis 1997). At the country-level, data on regulatory regimes or patent applications could be used to identify the reasons for the variation in firm-level takeoff between countries. Again, the scarcity of available data is a limiting factor of this type of research.

Appendix

Appendix 3.1: Correlation matrix

	TO	AT	AFT	DIS	CO	HI	MI	FM	EF	ENT	DSL	CAB	INC	GDP	POP	T1	T2	T3
TO	1																	
AT	0.03	1																
AFT	-0.03	-0.23	1															
DIS	-0.04	-0.27	0.17	1														
CO	-0.06	0.04	0.22	0.07	1													
HI	0.04	-0.06	0.34	0.08	0.17	1												
MI	-0.03	0.03	-0.27	-0.10	-0.06	-0.75	1											
FM	0.05	-0.09	-0.45	0.14	-0.34	-0.14	0.08	1										
EF	0.03	0.10	-0.33	-0.12	-0.15	-0.03	-0.09	-0.19	1									
ENT	-0.06	-0.06	0.61	0.38	0.57	0.35	-0.22	-0.48	-0.27	1								
DSL	0.08	0.02	-0.04	-0.08	-0.03	-0.07	-0.06	0.00	0.00	-0.05	1							
CAB	-0.07	0.01	-0.09	-0.08	-0.13	0.06	0.06	0.10	0.05	-0.19	-0.73	1						
INC	0.13	-0.06	-0.28	0.00	-0.27	-0.20	0.05	0.28	0.11	-0.29	0.41	-0.33	1					
GDP	0.02	0.07	-0.18	-0.17	-0.10	-0.35	0.11	0.08	0.12	-0.26	-0.01	0.02	0.10	1				
POP	0.11	0.04	0.05	-0.01	-0.08	0.09	-0.13	0.04	-0.02	-0.03	0.03	-0.04	0.06	-0.01	1			
T1	-0.03	0.01	-0.09	-0.05	0.25	-0.07	0.03	0.00	0.01	-0.06	-0.07	0.09	-0.11	-0.06	-0.07	1		
T2	-0.03	0.02	-0.10	-0.06	0.22	-0.07	0.03	0.01	0.01	-0.07	-0.06	0.09	-0.09	-0.06	-0.05	0.96	1	
T3	-0.02	0.02	-0.10	-0.06	0.20	-0.06	0.02	0.02	0.02	-0.08	-0.05	0.09	-0.08	-0.06	-0.04	0.90	0.98	1

Note: TO = takeoff (event variable), AT = entry at category takeoff, AFT = entry after category takeoff, DIS = distance entry to category takeoff, CO = competitors, HI = high income, MI = upper middle income, FM = first mover, EF = early followers, ENT = market entry order, DSL = DSL operator, CAB = cable operator, INC = incumbent operator, GDP = GDP growth, POP = population density.

Appendix 3.2: Descriptive statistics on time-to-takeoff

Country	Mean ttt	Median ttt	STD ttt	Country	Mean ttt	Medi-an ttt	STD ttt
Albania	NA	NA	NA	Moldova	9	9	NA
Algeria	7	7	NA	Monaco	1	1	NA
Argentina	14	15	1.73	Montenegro	3	3	NA
Australia	11.6	7	7.09	Morocco	5	5	NA
Austria	7.67	9	2.31	Netherlands	16	14	8.64
Bahrain	1	1	NA	New Caledonia	1	1	NA
Belarus	3	3	NA	New Zealand	15	15	7.07
Belgium	12.25	11	5.56	Nicaragua	NA	NA	NA
Bolivia	NA	NA	NA	Norway	8.5	8	1.73
Brazil	30	30	NA	Oman	1	1	NA
Bulgaria	12.67	11	9.61	Pakistan	NA	NA	NA
Canada	12.75	12	2.36	Panama	1	1	NA
Chile	14.5	14.5	7.78	Peru	16.5	16.5	7.78
China	26.67	26	7.02	Philippines	18	18	NA
Colombia	17.5	16	6.19	Poland	14.5	14.5	6.36
Czech Republic	10	8	6.24	Portugal	11.25	10	6.5
Denmark	6.2	3	4.97	Qatar	1	1	NA
Egypt	21	21	NA	Romania	11	11	1.41
Estonia	3	3	2	Russia	20	20	NA
Finland	7	9	4.36	Saudi Arabia	18	18	NA
France	7.86	7	7.84	Senegal	8	8	NA
Germany	13.67	16	6.81	Singapore	6	6	5.66
Greece	6	5.5	3.16	Slovak Republic	4	4	NA
Hong Kong	4	5	2.35	South Africa	10	10	NA
Hungary	16.6	15	5.81	Spain	12.8	12	7.6
Iceland	3	3	2.83	Sri Lanka	17	17	NA
India	NA	NA	NA	Suriname	8	8	NA
Indonesia	23	23	NA	Sweden	13.5	13.5	9.19
Ireland	9	9	4.24	Switzerland	5.5	5.5	2.38
Italy	6.25	7	4.11	Syrian Arab Republic	NA	NA	NA
Jamaica	14	14	NA	Thailand	18	18	NA
Japan	7.5	3	7.84	Tunisia	7	7	NA
South Korea	4.57	4	3.08	Turkey	14	14	NA
Latvia	20	20	14.14	Ukraine	20	20	NA
Liechtenstein	1	1	NA	United Kingdom	11.33	10	5.66
Lithuania	5.4	5	4.56	United States	20.33	19	3.21
Luxembourg	4	4	0	Uruguay	8	8	NA
Macedonia	8	8	NA	Venezuela	18	18	NA
Malta	2	2	1.41	Vietnam	9	9	NA
Mauritius	9	9	NA	Yemen	NA	NA	NA
Mexico	11	11	NA				

Note: Mean indicates the mean time-to-takeoff over all firms reaching firm-level takeoff in one country; NA if no firm-level takeoff is observed in the country; std is NA if only one firm-level takeoff is observed in country; ttt = time-to-takeoff; STD = standard deviation.

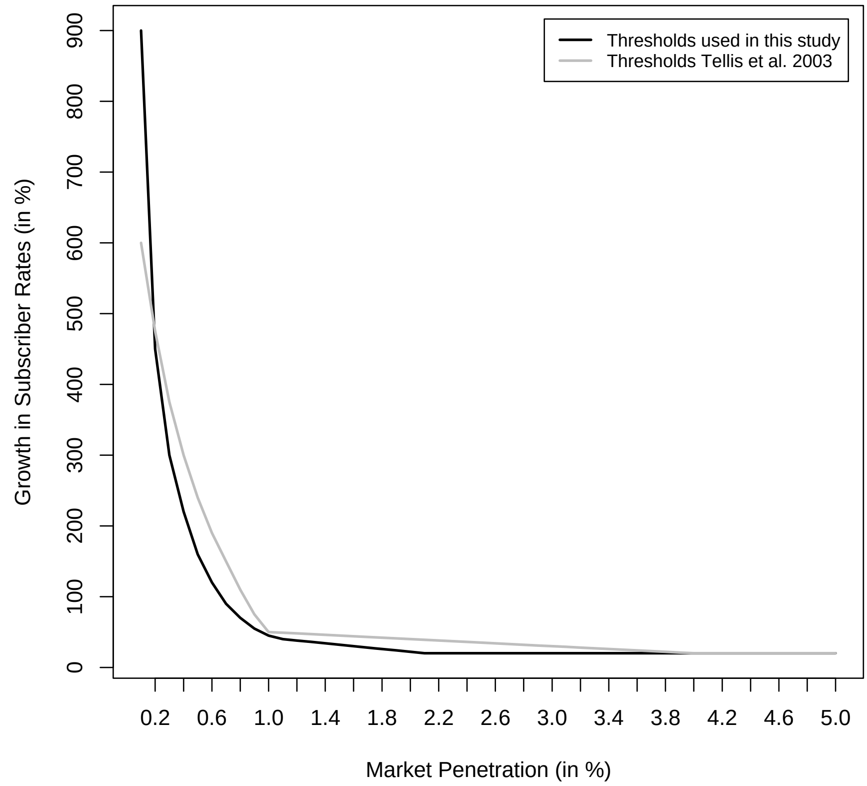
Appendix 3.3: Descriptive statistics on the occurrence of takeoff

Country	Number of firms	Takeoffs observed	No takeoff observed	Firm-level takeoff before category-level takeoff	Firm-level takeoff after category-level takeoff	Firm-level takeoff at category-level takeoff
Albania	1	0	1	0	0	0
Algeria	1	1	0	0	0	1
Argentina	5	3	2	0	3	0
Australia	6	5	1	0	5	0
Austria	5	3	2	0	2	1
Bahrain	1	1	0	0	0	1
Belarus	1	1	0	0	0	1
Belgium	7	4	3	0	4	0
Bolivia	1	0	1	0	0	0
Brazil	11	1	10	0	1	0
Bulgaria	4	3	1	0	3	0
Canada	6	4	2	0	4	0
Chile	7	2	5	0	2	0
China	8	3	5	0	3	0
Colombia	10	4	6	0	4	0
Czech Republic	6	3	3	0	2	1
Denmark	14	5	9	0	5	0
Egypt	1	1	0	0	0	1
Estonia	6	3	3	0	2	1
Finland	4	3	1	0	2	1
France	20	7	13	0	7	0
Germany	15	3	12	0	2	1
Greece	4	4	0	0	3	1
Hong Kong	5	5	0	0	4	1
Hungary	10	5	5	0	5	0
Iceland	2	2	0	0	1	1
India	10	0	10	0	0	0
Indonesia	1	1	0	0	0	1
Ireland	5	2	3	0	1	1
Italy	7	4	3	0	3	1
Jamaica	1	1	0	0	0	1
Japan	10	6	4	0	3	3
Latvia	5	2	3	0	2	0
Liechtenstein	1	1	0	0	0	1
Lithuania	10	5	5	0	5	0
Luxembourg	4	2	2	0	1	1
Macedonia	1	1	0	0	0	1
Malta	2	2	0	0	1	1
Mauritius	1	1	0	0	0	1
Mexico	5	1	4	0	0	1
Moldova	1	1	0	0	0	1
Monaco	1	1	0	0	0	1
Montenegro	1	1	0	0	0	1
Morocco	1	1	0	0	0	1
Netherlands	14	7	7	0	7	0
New Caledonia	1	1	0	0	0	1
New Zealand	2	2	0	0	1	1
Nicaragua	1	0	1	0	0	0
Norway	5	4	1	0	4	0
Oman	1	1	0	0	0	1

Appendix 3.3 (continued)

Pakistan	3	0	3	0	0	0
Panama	1	1	0	0	0	1
Peru	4	2	2	0	1	1
Philippines	3	1	2	0	1	0
Poland	16	2	14	0	2	0
Portugal	4	4	0	0	4	0
Qatar	1	1	0	0	0	1
Romania	4	2	2	0	2	0
Russia	12	1	11	0	1	0
Saudi Arabia	1	1	0	0	0	1
Senegal	1	1	0	0	0	1
Singapore	2	2	0	0	2	0
Slovak Republic	5	1	4	0	1	0
South Africa	6	1	5	0	1	0
South Korea	23	14	9	0	14	0
Spain	13	5	8	0	5	0
Sri Lanka	1	1	0	0	0	1
Suriname	1	1	0	0	0	1
Sweden	9	2	7	0	2	0
Switzerland	5	4	1	0	4	0
Syrian Arab Republic	1	0	1	0	0	0
Thailand	2	1	1	0	0	1
Tunisia	1	1	0	0	0	1
Turkey	7	1	6	0	1	0
United Kingdom	16	9	7	0	9	0
Ukraine	3	1	2	0	1	0
Uruguay	1	1	0	0	0	1
United States	22	3	19	0	3	0
Venezuela	1	1	0	0	0	1
Vietnam	6	1	5	0	1	0
Yemen	1	0	1	0	0	0

Appendix 3.4: Operationalization of takeoff



Note: This figure shows the operationalization we used in comparison to the operationalization Tellis et al. (2003) applied. Thereby, firm-level takeoff occurs in the year the firms' growth in subscriber rates (y-axis) crosses the threshold shown in relation to market penetration (x-axis). It is noticeable that both threshold curves are very similar. However, the threshold curve of Tellis et al. (2003, grey graph) gives stricter growth-penetration combinations to match in order to reach takeoff.

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4 The Dynamic Effects of Relational and Transactional Selling Strategies on Salesperson Performance

Abstract

Many firms rely heavily on the success of their salespersons. Hence, analyzing the drivers of salesperson performance has gained considerable attention in the marketing literature. However, studies thus far have widely neglected the dynamic effects of building long-term salesperson-customer relationships and leveraging transactional marketing elements. Filling this research gap, this paper uses a unique dataset covering eight and a half years of monthly sales records for 812 independent salespersons. Applying growth curve modeling to analyze the performance trajectories of individual salespersons, the study reports the following results: (1) the functional form of the relationship between relational selling strategy and salesperson performance has an inverted U-shape, i.e., the impact of this relationship increases with time; (2) price specialization enhances performance, but its importance decreases with time; (3) product specialization and (4) selling more in advance both increase salesperson performance and the importance of both effects increases with time; (5) geographic proximity enhances salesperson performance regardless of time. We address the implications of these results in detail and illustrate how sales managers can assess individual salesperson performance.

Keywords: *Salesperson performance, selling strategy, longitudinal study, dynamic effects, growth curve analysis*

Publication note: This paper has been submitted to the Journal of Marketing. Co-authors of this paper are Markus Meierer and René Algesheimer.

4.1 Introduction

Many firms rely heavily on the success of their salespersons. Salespersons build the direct link between a firm and its prospective and existing customers. Hence, analyzing drivers of salesperson performance has gained considerable attention in the marketing literature (e.g., Ahearne et al. 2013b, Churchill et al. 1985, Franke and Park 2006, Homburg et al. 2011a, Verbeke et al. 2011). However, studies thus far have widely neglected the dynamic effects of building long-term salesperson-customer relationships and leveraging transactional marketing elements.

An important driver of salesperson performance is a salesperson's ability to build trusting and lasting relationships with customers to generate repeat purchases. Since the seminal work of Berry (1983) on relationship marketing, it is widely quoted that the "returns to loyalty are in double-digit categories" (Oliver 1999, p. 43). Anecdotal evidence from interviews with sales managers suggests that a strong relationship exists between the number of repurchases and salesperson performance. Especially for salespersons with a long tenure at a firm, customer relationships become increasingly important. Thus, building relationships with customers has moved up on the agenda of many marketers (Rust et al. 2010). However, empirical evidence on the impact of the level of repurchases on salesperson performance does not exist.

The existing literature supports our assumption that adopting a relational selling strategy positively affects salesperson performance. Over the last three decades, many studies have illustrated the importance of relationship marketing and have, thus, challenged and complemented the traditional marketing paradigm (Grönroos 1990, Palmatier et al. 2006). We draw on this research by highlighting two particular findings: (1) establishing relationships with customers brings long-term benefits to a firm (Reinartz et al. 2005, Reinartz and Kumar 2000, Reinartz and Kumar 2003, Verhoef et al. 2007), and (2) salespersons play an important role in this context (Palmatier et al. 2007). In addition, studies have recognized that customer relationships evolve over time because of the development of trust in the salesperson and the products (Lewin and Johnston 1997). By modeling the dynamic effects of a salesperson's relational selling strategy on salesperson performance, we extend the work by Palmatier et al. (2013) who highlight the importance of taking a dynamic perspective when analyzing the influence of relational constructs on performance.

In addition to the relational selling strategy, a **salesperson's transactional selling strategy**, i.e., the ability to sell well, remains a cornerstone of the salesperson's success (Churchill et al. 1985, Johnson and Sohi 2013, Verbeke et al. 2011). The key principle of all marketing-driven businesses is to meet customers' needs, which is accomplished by selling the right product at the right time in the right place (Li et al. 2011). In this context, salespersons play an important role. They are the face of the company and must assess and satisfy the needs of existing as well as future customers. In this process, they identify and evaluate alternative solutions together with the customer to select the most appropriate solution. However, salespersons are continuously weighing the opportunity costs of their efforts (Simonson 2005). For example, salespersons must assess the costs and benefits if they have to create a highly customized offer, if a sale involves a product beyond their area of expertise (e.g., selling travel products or services outside a certain price range), or if a sale would require the salesperson to travel an unusually long distance to the customer.

The decision depends on the **importance of these transactional drivers for salesperson performance, which may vary by individual and over time**. In the case of a travel agent, for example, the actual positioning in the market (e.g., if a travel agent focuses on offerings within a certain price range or mainly recommends offerings from a specific set of travel operators), the timing of approaching the customer, and the geographic proximity of the salesperson to the customer are potential drivers of success. Sales managers must monitor the general impact of these transactional drivers of salesperson performance (Shannahan et al. 2013) and identify both weaknesses and strengths of each individual salesperson. So far, research did not consider the dynamic effects of these transactional drivers on salesperson performance.

Taking a firm-level perspective, Kirca et al. (2005) highlight the **importance of assessing both relational and transactional elements** as integral parts of a management information system. Based on a meta-analysis of 114 studies, the authors reveal the particular usefulness of tracking the relationships between performance and customer loyalty, service quality, and product quality. Acknowledging the importance of relational and transactional elements for the sales process and considering the dynamic nature of salesperson performance and its drivers, our study adds to existing literature by analyzing the following research questions:

1. How does a salesperson's relational selling strategy influence salesperson performance?
2. How does a salesperson's transactional selling strategy influence salesperson performance?
3. What are the dynamics of both relationships?

By answering these questions, we provide the first insights into the dynamic nature of two important salesperson performance drivers and derive implications for research and practice.

Our study differs from previous literature from a substantial, data, and methodological perspective. First, this study emphasizes the dynamic effects of relational and transactional selling strategies on salesperson performance. Specifically, using a contingency framework and relying on relationship marketing and traditional marketing theory, we derive hypotheses regarding the determinants of salesperson performance over time. Second, to the best of our knowledge, this study is the first attempt to analyze salesperson performance with longitudinal data over several years. At the same time, we use objective measures as time-varying covariates. Thus, our study extends previous work, which relies on subjective measures obtained through survey data (Ahearne et al. 2010, Fu et al. 2010). We use monthly sales data for 812 independent salespersons in the tourism industry from 2005 to 2013. Third, we apply a random effects approach to analyze our hypotheses. This approach not only facilitates a more rigorous evaluation of statistical effects (Hofmann 1997, Peterson et al. 2012, Steenbergen and Jones 2002), but also allows practitioners to contrast individual salesperson performance with the average salesperson performance.

Our **main empirical findings are as follows**: (1) The functional form of the relationship between relational selling strategy and salesperson performance has an inverted U-shape. The impact of this relationship changes over time, i.e., the impact of adopting a relational selling strategy increases with a salesperson's tenure. With regards to a salesperson's transactional selling strategy, we find that (2) price specialization enhances salesperson performance, but its importance decreases with time. Further, (3) product specialization and (4) selling more in advance both increase salesperson performance whereby the importance of both effects increases with time. Regardless of time, (5) geographic proximity enhances salesperson performance.

The **remainder of this paper** is organized as follows: In the second section, we review the relevant literature on salesperson performance highlighting the scarcity of longitudinal studies, and illustrate the importance of considering the dynamic nature of salesperson performance. In the third section, we outline the conceptual background of the study and formulate the hypotheses. In the fourth section, we present our data and measurement and discuss the analytical procedure. In the fifth section, we outline the results in detail. In the last section, we conclude by presenting managerial implications offering application-oriented examples, and providing suggestions for further research.

4.2 Relevance of a dynamic salesperson performance assessment

Although dynamic in nature, the vast **majority of studies on salesperson performance are cross-sectional analyses**. They mostly use subjective performance measures, such as self-ratings or supervisor-ratings of salesperson performance (for an overview, see Appendix 4.1). Fewer cross-sectional studies apply one-time objective measures of salesperson performance, such as volume of annual sales (e.g., Homburg et al. 2011c, Kidwell et al. 2011), percentage attainment of sales quotas (e.g., Ahearne et al. 2013a, Hughes 2013), salesperson performance for particular brands (e.g., Hughes and Ahearne 2010), or a performance measure including weekly average call handling time, conversion rate, and customer satisfaction (e.g., Jasmand et al. 2012). The importance of differentiating between subjective and objective measures has been highlighted previously (Bommer et al. 1995). The determinants of salesperson performance analyzed in these cross-sectional studies are almost entirely based on survey data (see Appendix 4.1 for an overview).

Very few longitudinal studies have analyzed salesperson performance.[1] To the best of our knowledge, only two studies have examined salesperson performance by using longitudinal sales data covering a long time period (see Table 4.1). First, Ahearne et al. (2010) analyze how salespersons' goal orientation influences their performance trajectories during a period of change, e.g., the introduction of new sales technology. The authors regress monthly sales on attitudinal data measured by a one-time survey administered in the month preceding the actual sales technology rollout. Second, Fu et al. (2010) examine salespersons' attitudes towards selling a new-to-market product and a line extension by analyzing the daily sales volumes of salespersons over a period of 457 days and 304 days respectively. The authors also obtain salesperson's attitudinal measures from a survey administered with salespersons in the month

[1] A few studies analyze performance by using data from two-wave surveys, but use performance measures other than actual sales. For example, Johnston et al. (1990) analyze the influence of leadership behavior, role ambiguity, and job satisfaction on employee turnover by using data from a two-wave survey. In addition, Brown et al. (1997) examine the effects of goal-directed emotions on salesperson volition, behavior, and performance (i.e., outcome emotions).

preceding the launch of the new products. Both studies make a strong contribution to the literature by explicitly accounting for the dynamic nature of salesperson performance. However, the studies are limited by the characteristics of their data. Using time-invariant measures as determinants of salesperson performance, they cannot fully capture the dynamics of the hypothesized relationships. This issue has been highlighted by Palmatier et al. (2013) who focus on the dynamics of drivers of salesperson performance, but only take a static perspective with regards to sales revenue. Our study complements those studies by analyzing both the dynamics of drivers as well as salesperson performance over multiple periods.

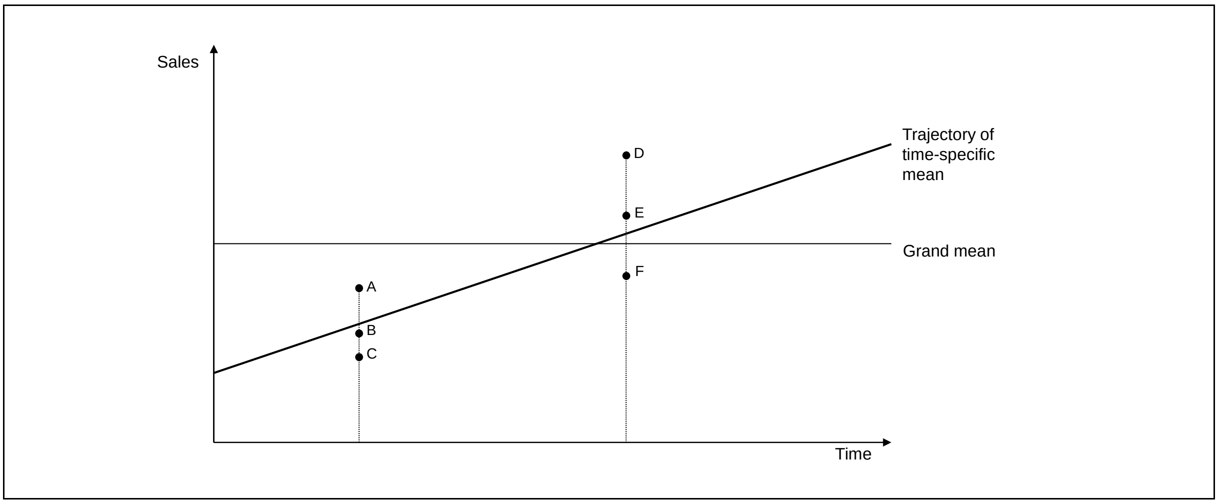
Table 4.1: Longitudinal studies on salesperson performance

Study	Performance measurement	Determinants	Time-varying determinants
Ahearne et al. (2010)	Monthly sales data over 12 months (N = 400), polynomial growth model	Goal orientation during a period of change (obtained via a survey in the month preceding the actual sales technology rollout)	No
Fu et al. (2010)	Daily sales volume per salesperson over 457 days for a new-to-market product (N = 308), 304 days for the line extension (N = 226), polynomial growth model	Subjective norms, attitudes, self-efficacy, moderated through selling intentions (obtained via a survey in the month preceding new product launch)	No
This study	*Monthly sales data over 8.5 years (N = 812), linear growth model*	*Salespersons' relational and transactional selling strategies (obtained from company records)*	*Yes*

Why is measuring salesperson performance over time important? In general, monitoring salesperson performance is the highest priority task for sales manager, as this information helps to make decisions regarding which salespersons should be considered for rewards, specific trainings, or even contract terminations. Although neglected by practitioners and academics, the dynamic nature of salesperson performance must be considered to (1) set appropriate benchmarks for evaluating a salesperson's current performance, (2) determine a salesperson's developmental trajectory to assess his or her future performance, and (3) account for the influence of contextual effects on salesperson performance.

First, **setting appropriate benchmarks is crucial for evaluating a salesperson's current performance**. An underperforming salesperson may actually outperform when the time dependency of a salesperson's current performance (e.g., its variation with salesperson tenure) is explicitly considered. Figure 4.1 shows the sales of six salespersons (A to E). Regarding the average sales over time for all salespersons (grand mean), salespersons D and E outperform, and salespersons A, B, C, and F underperform. However, if the average sales level is examined at each point in time, the results change. Salesperson A also outperforms when a dynamic benchmark is applied (i.e., salesperson A outperforms the time-specific mean).

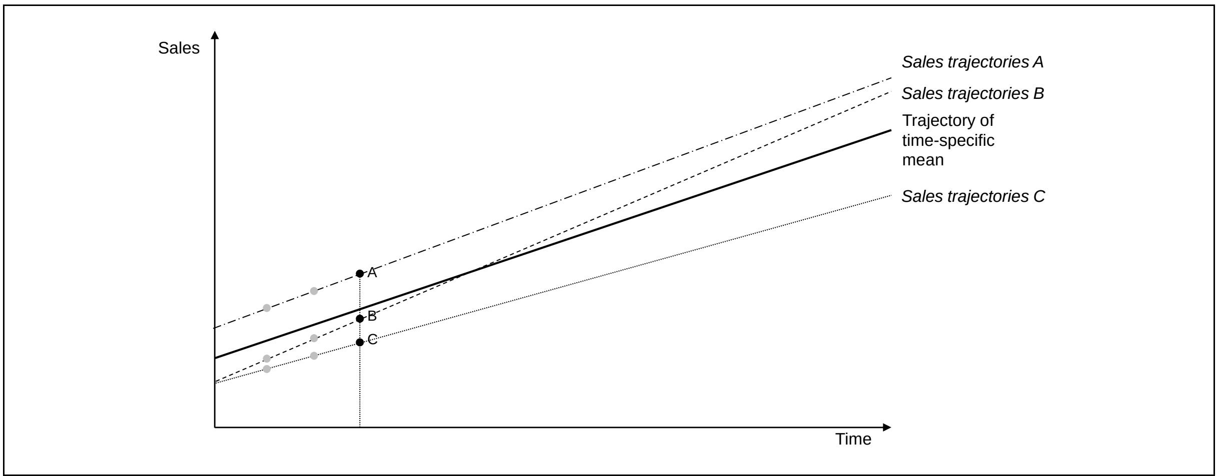
Figure 4.1: Setting an appropriate benchmark for current performance assessment



Note: Author's own representation.

Second, **accounting for developmental trajectories in evaluating future performance** is important to assess whether a salesperson is "on the right track". Based on a salesperson's sales history, an individual developmental trajectory can be derived. Figure 4.2 illustrates the sales development of three salespersons (A to C). For salesperson B, the current performance is below average; however, an examination of the developmental trajectory indicates a positive outlook for the near future. In contrast, salesperson C underperforms the others in terms of not only current sales but also future sales growth.

Figure 4.2: Considering developmental trajectories to assess future performance



Note: Author's own representation.

Third, the **impact of time-invariant and time-varying contextual factors** should be considered to adequately evaluate salesperson performance. Benchmarks for performance evaluation must account for factors that are largely unchangeable for both sales managers and salespersons, e.g., competition or seasonality. Controlling for these contextual factors, it is possible to disentangle the impact of "influenceable factors" on salesperson performance (Churchill et al. 1985).

4.3 Conceptualization and hypotheses development

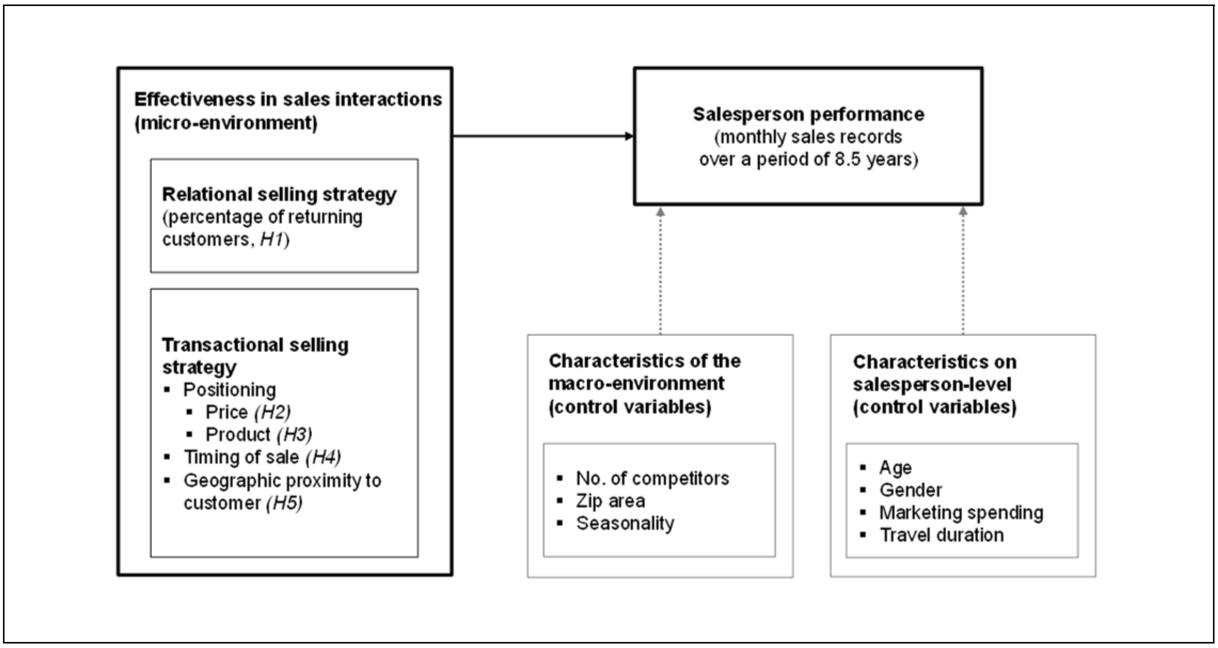
4.3.1 Conceptual framework

The **conceptual framework underlying our analysis builds on contingency theory** and previous research (see Figure 4.3). Weitz (1981) introduced a contingency framework for understanding salesperson performance arguing that a salesperson's effectiveness depends on micro- and macro-environmental factors. Since then, multiple studies have used contingency theory to analyze sales performance (e.g., Homburg et al. 2011b, Hughes et al. 2013). Drawing on this research, our study focuses on analyzing the influence of micro-environmental factors (i.e., effectiveness in sales interaction) while controlling for a variety of external effects (e.g., competitive intensity).

We **account for the effectiveness in sales interactions in two ways**. By distinguishing between salespersons' relational and transactional selling strategies, we draw on previous research (Saxe and Barton 1982, Voss and Voss 2008). We define a salesperson's relational selling strategy as the salesperson's effectiveness in building lasting relationships. This is reflected by the number of returning customers. A salesperson's transactional selling strategy is defined as the salesperson's effectiveness during the sales process. Clear positioning (e.g., in terms of price and product specialization), the ability to address customers at the right time, and optimal geographic proximity to the customer increase the effectiveness of a salesperson's transactional selling strategy.

We **control for the influence of not only several macro-environmental factors but also salesperson characteristics**. Regarding macro-environmental influences, the characteristics of the sales area, such as the competitive intensity or the location of the salesperson, may influence salesperson performance. Further, characteristics of the salesperson, such as age or gender, have to be considered.

Figure 4.3: Conceptual framework



4.3.2 Relational selling strategy

From a theoretical perspective, the **traditional view of marketing as a transactional process has long been replaced by a more integrative and relationship-oriented view** (e.g., Grönroos 1997, Kotler and Levy 1969, Van Waterschoot and Van den Bulte 1992, Vargo and Lusch 2004). The shift from tangible resources and transactions to intangible resources, co-creation, and relationships has led to a shift in perspectives among marketing scholars (e.g., Berry 1995, Grönroos 1995, Vargo and Lusch 2004, Webster 1992). Accordingly, exchange processes have become a central determinant of product success (Ailawadi et al. 2003, Srivastava et al. 1999). Thus, an efficient service marketing strategy now concerns not only selling products but also keeping customers by building trusting relationships.

Previous studies have widely discussed the importance of customer retention for performance and the adoption of the right marketing strategy (e.g., Blattberg and Deighton 1996, Reinartz et al. 2005, Thomas 2001, Wang and Splegel 1994). With a more mature relationship, customers can acquire more information and obtain a better impression of the product (Verhoef et al. 2002). Consistent with this reasoning, Reinartz and Kumar (2003) find that longtime customers have higher spending levels than newer customers. Thus, to achieve better sales performance, firms must direct their effort toward specific customers, not necessarily all possible customers (Dowling and Uncles 1997). However, disproportionately focusing on customer retention – and neglecting the influence of the customer acquisition process on the customer retention process – may be an ineffective strategy (Thomas 2001). Therefore, firms must achieve an appropriate balance between returning and newly acquired customers, as finding an optimal level of retention (in relation to acquisition) can enhance salesperson performance.

The **dynamic nature of relationships** has been examined in previous work on firm performance, but is widely neglected in the context of salesperson performance. In the context of retail, Jap and Ganesan (2000) note that the effectiveness of relationship strategies changes over the course of a relationship and that dynamic effects should be accounted for over the duration of the customer-firm relationship. In a longitudinal analysis of salesperson performance in particular, the evolution of relationships should be considered because customers develop trust in the salesperson and the products over time (Lewin and Johnston 1997). Analyzing the impact of relationship velocity on salesperson performance, Palmatier et al. (2013) highlight the importance of a dynamic assessment of relational performance drivers.

We **consider an inverted U-shaped relationship between a salesperson's relational selling strategy and salesperson performance, which interacts with time.** This effect indicates that the optimal ratio of returning and acquired customers depends on the salesperson's tenure in the market. Knowing the optimal level of returning customers at every point in time enables salespersons to effectively adapt their efforts in a dynamic way. We rely on the framework by Weitz (1981) and explicitly consider relationship strategy as a driver of salesperson performance. By disentangling the dynamic relationship between both, we extend existing literature which has a strong focus on determinants of relationship building, but neglects its impact on salesperson performance. Thus, we propose the following:

H1: *(a) A salesperson's relational selling strategy influences the salesperson's performance through an inverted U-shaped relationship. (b) This influence increases with the salesperson's tenure.*

4.3.3 Transactional selling strategy

From a theoretical perspective, **previous studies have elaborated how a clear positioning creates a competitive advantage** (Dess and Davis 1984, Porter 1980). Signaling product expertise and lowering costs by addressing recurrent familiar situations are two important advantages of specialization, particularly in the service industry (Kotler and Connor Jr. 1977). Further, according to cognitive selling research, salespersons are more effective when they can rely on explicit scripts that are suitable for specific selling situations, which allow salespersons to immediately adapt their selling strategy to the specific selling context (Porter and Inks 2000). Consequently, firms have transitioned from encouraging salespersons to sell all of a firm's products to fostering specialization among salespersons (Weitz and Bradford 1999).

Previous research on salesperson performance has considered various effects related to a salesperson's ability to sell the right product. Ahearne et al. (2007), for example, find that sales presentation skills significantly influence salesperson performance. In addition, a salesperson's ability to present a product in a relevant, comprehensive, and customer-oriented manner is an important factor driving performance (Verbeke et al. 2008). Other studies show the effects of product knowledge, experience, and familiarity with the product and service on salesperson performance (Ahearne et al. 2013b, Rapp et al. 2006). However, positioning as such has not been considered in earlier work.

We **consider two aspects of a positioning strategy**: price positioning and product positioning. Specialized salespersons with a more distinct knowledge base will perform better than salespersons with a broad and general but not specific knowledge base. Additionally, salespersons will expand their knowledge over time. To account for dynamics in a salesperson's positioning strategy, we explicitly consider the role of salesperson tenure as a moderator of the relationship between a salesperson's positioning strategy and salesperson performance. Thus, we propose the following hypotheses:

H2: (a) Price positioning positively influences salesperson performance. (b) This influence increases with the salesperson's tenure.

H3: (a) Product positioning positively influences salesperson performance. (b) This influence increases with the salesperson's tenure.

Addressing customers at the right time is crucial for salesperson performance. This factor is particularly important if product consumption is temporally separated from the actual time of purchase as with many services (Shugan and Xie 2000, Simonson 1990). For example, travel products and services, airline tickets, and tickets for concerts or sporting events are all purchased well in advance. These exchanges have been described as advance selling situation (Shugan and Xie 2000).

From a **state-dependent utility theory** perspective, buyers are uncertain about the value that they receive from a service at the time of consumption (Shugan and Xie 2000). Consequently, consumers predict their preferences and the future utility and can control when to purchase a product (Cooke et al. 2001, Simonson 1992). In this way, earlier buyers are more price sensitive than later buyers who purchase products or services closer to the time of consumption (Xie and Shugan 2001). Furthermore, limited availability plays an important role, particularly in the service industry. For example, flights or concerts that are scheduled for specific dates can be sold out in advance. Additionally, prices may increase, e.g., early bird travel discounts are available only for a limited period. Thus, at the point of purchase, a customer's risk of not receiving the service or paying a price premium must compensate for this uncertainty, which eventually leads to a purchase decision.

Prior research has shown that sellers enjoy, on average, greater sales volume from advance sales than from sales in the spot period because of higher prices of the latter (Shugan and Xie 2000, Xie and Shugan 2001). In a later study, Fay and Xie (2010) show that "offering advance sales encourages customers to purchase while they are uncertain about their consumption states" (p. 1040). Furthermore, proposing the right product at the wrong time to a customer could result in a lost sale (Kumar et al. 2008). Thus, salespersons must anticipate the best time to offer a product to a customer to guarantee the best possible sales.

We **consider the timing of the sale** by analyzing how far in advance of the actual consumption salespersons sell services to the customer. In accord with theory and previous research, we argue that selling further in advance improves salesperson performance. Considering timing as a dynamic driver of salesperson performance, we argue that with a longer tenure the salesperson will gain a sense of the best timing for an offer. Thus, we propose the following:

H4: (a) Selling timely positively influences salesperson performance. (b) This influence increases with the salesperson's tenure.

According to **location theory research**, "retailers and services should locate in convenient locations that allow easy access and attract the largest number of customers" (Jones et al. 2003, p. 702). Greater distance to the service provider decreases the utility for the consumer, which reduces the likelihood that the consumer selects the service provider. Furthermore, the more travelling a salesperson must do to reach the customer, the less the salesperson can focus on preparing and selling offerings to the customer (Anderson 2008), which may decrease sales potential.

Previous studies from service research have highlighted the effect of sales territory design (e.g., the sales manager's assignment of salespersons to geographic sales areas) on salespersons' performance (Babakus et al. 1996, Grant et al. 2001). Additionally, managing customers from different geographic locations affects the management of service quality because its importance may vary spatially (Mittal et al. 2004). Studies on service convenience show how location and access convenience predict repurchase intention (Berry et al. 2002, Colwell et al. 2008, Seiders et al. 2007). Geographic proximity to the service provider is also found to lower customers' tendency to switch providers (Keaveney 1995, Lee and Cunningham 2001). Despite the existing literature, the influence of the geographic proximity between a salesperson and customers on salesperson performance has not yet been analyzed.

Applying these results to our context, we assume that close proximity between the customer and the salesperson enhances the likelihood and simplifies the process of attracting customers, which improves salesperson performance. We further consider the dynamics of this relationship and argue that with increasing process standardization over time, the salespersons can save time in preparing offers which in turn can be used to market to an expanded sales area. Thus, we propose the following hypothesis:

H5: (a) A closer geographic proximity between the salesperson and the customer positively influences salesperson performance. (b) This influence decreases with the salesperson's tenure.

4.4 Method

4.4.1 Data collection

This study **analyzes monthly sales data for the period from April 2005 to September 2013** for 812 independent salespersons from a subsidiary of one of the largest European tourism operators. This branch was founded in April 2005; thus, the data include all the available sales data for the salespersons working for this branch since its founding. All the salespersons operate under the same brand but work independently in the sense that they are responsible for their own actions, e.g., their own marketing. The company's headquarters provides standardized marketing material, but salespersons must request and pay for this material as needed. All product prices are fixed, i.e., salespersons cannot negotiate individual discounts with their customers. The salespersons do not receive fixed salaries; rather shares of the revenues that they generate are divided between them and the company's headquarters. All the salespersons report to the same sales manager. The sales manager's team provides the administrative back end for fulfilling orders. Because the firm assigns sales areas, no competition exists among salespersons. Previous studies on independent salespersons include Joshi and Randall (2001), Thompson et al. (1992), and Venkatesh et al. (2001).

Data were obtained from two sources: company records and external data on market characteristics. The company records contain three groups of variables: the monthly sales of each salesperson (i.e., the sum of all the prices of the transactions made), selling strategy-related variables, and salesperson characteristics (e.g., gender and age). Furthermore, the firm granted limited access to individual transaction data to derive particular determinants of salesperson performance. To include effects based on the market environment, we also obtained data on competitive intensity from external sources.

4.4.2 Measurement

Table 4.2 provides an **overview of the variables included in the growth curve model and their measurements**. A detailed discussion is presented in the text that follows. A correlation matrix and further descriptive statistics can be found in Appendix 4.2 and Appendix 4.3 respectively.

The **dependent variable** in our analysis is salesperson performance. We obtain monthly sales for each salesperson from the company's records to establish the growth rate of sales for each salesperson. For our model, we use the logarithm of sales.

The **effect of time** is represented by salesperson tenure, i.e., the number of months since the salesperson joined the firm (Biesanz et al. 2004). Thus, we include a linear effect of time. Time is centered at time point 12.

A **salesperson's relational selling strategy** is indicated by the amount of business that a salesperson conducts with returning customers. Examining each individual transaction, we determine whether the customer was newly acquired or whether the customer had transacted with the salesperson previously. Then, we derive the percentage of returning customers among all customers by salesperson and month. Rust et al. (1995) highlight that customer retention measures are ideally obtained from a database, although such data are rarely available to firms and researchers.

Table 4.2: Overview of the variables included in the model and their measurement

Variable	Measurement
Dependent variable	
Salesperson performance	Monthly sales of salesperson (log-transformed variable)
Independent variables	
Level 1 (time-varying)	
Effect of time	
Time	Month the salesperson is active, centered at time point 12
Relational selling strategy	
Returning customers	Percentage of repeated transactions by salesperson and month (i.e., ratio of returning customers)
Returning customers × time	Interaction effect between the effect of returning customers and time (i.e., a salesperson's tenure in the market)
Returning customers^2	Quadratic effect of the percentage of repeated transactions by salesperson and month
Returning customers^2 × time	Interaction effect between the quadratic effect of returning customers and time
Transactional selling strategy	
Price positioning	Relative absolute mean deviation of the logarithm of price per person per day of all transactions by salesperson and month
Price positioning × time	Interaction effect between price positioning and time
Product positioning	Normalized version of the number of travel operators sold by salesperson and month
Product positioning × time	Interaction effect between product positioning and time
Timing of the sale	Median time difference between the transaction date and the start date of travel for all transactions by salesperson and month
Timing of the sale × time	Interaction effect between timing of sale and time
Geographic proximity	Median geographic distance (in km) between salesperson and all customers who purchased travel offerings with this salesperson during one month
Geographic proximity × time	Interaction effect between geographic proximity and time
Control variables	
Level 1 (time-varying)	
Seasonality	Binary variables for each month (reference category is January)
Marketing spending	Marketing spending of a salesperson in the past six months
Travel duration (of the trips sold)	Median length of travel offerings sold by salesperson and month
Level 2 (time-invariant)	
Number of competitors	Number of travel agencies in salesperson's ZIP code in 2012
Salesperson's ZIP code area	Binary variables for each ZIP code area defined by the first digit of the postal code (reference category is the area starting with 0)
Age	Count variable indicating the salesperson's age
Gender	Binary variable indicating whether the salesperson is female

A salesperson's transactional selling strategy is represented by several factors. Accounting for the influence of *price positioning* on salesperson performance, we use the logarithm of the price per person per day for each individual transaction record. In this way, we explicitly account for the number of travel companions and the travel duration. We then take the relative absolute mean deviation of this variable as a robust, normalized measure of price variation. We argue that smaller variation indicates better positioning. This enables us to analyze the fundamental impact of price positioning whether a salesperson focuses mainly on low- or high-priced products. Furthermore, *product positioning* is operationalized as the number of unique travel operators sold by salesperson and month. For comparability reasons, this value is normalized by the number of transactions per month as follows:

$$\text{Product positioning}_{\text{normalized}} = \frac{\left(\dfrac{\text{number of operators}}{\text{number of transactions}} - \dfrac{1}{\text{number of transactions}}\right)}{\left(1 - \dfrac{1}{\text{number of transactions}}\right)} \qquad (4.1)$$

Additionally, we account for the *timing of the sale*, i.e., how far in advance the salesperson sells the product to the customer. Thus, we calculate the difference in days between the transaction date and the start date of travel for each individual transaction and derive the median by salesperson and month. Finally, we also consider *geographic proximity*. Based on the salesperson's and customer's ZIP code information, we calculate the geographic proximity in kilometers for each individual transaction by querying the Google Maps API (Google 2014) and derive the median by salesperson and month.

To account for the **characteristics of the external market environment**, we include several control variables. We operationalize the *number of competitors* as the number of travel agencies in a salesperson's ZIP code area. This approach is consistent with previous studies in the literature that have modeled competitive intensity (Voss and Voss 2008). We obtain data on all travel agencies for 2012 from an external database. Furthermore, to control for the *geographic location of the salesperson*, we include dummy variables for the salesperson's ZIP code area. Finally, consistent with previous research, we include dummy variables for *seasonality* effects indicating each month (Wooldridge 2012).

In addition, we **control for several characteristics at the salesperson level**. *Marketing spending* is operationalized as the monthly expenses for marketing articles and promotional material for a salesperson. This operationalization is in accordance with measures used in previous studies (Luo and Jong 2012, Sridhar et al. 2013, Van Heerde et al. 2013). This measure includes all marketing activities, i.e., activities aimed at acquiring new and retaining existing customers. Marketing spending is formulated as a stock variable, i.e., the sum of all marketing spending in the past six months. *Travel duration* is operationalized as the median length of a trip sold by salesperson and month. Additionally, consistent with prior research, we measure *age* as the age of the salesperson in years (Reinartz and Kumar 2003). This information was gathered from the birth dates indicated in the company records. In our analysis, age is mean centered. Finally, the *gender* variable indicates whether the salesperson is female.

4.4.3 Analytical procedure

Modeling the development of salesperson performance requires taking into account the **clustered data structure**, i.e., the monthly sales observations (level-one units) clustered by salespersons (level-two units). For this purpose, we employ a growth curve modeling approach to test our hypotheses (e.g., Raudenbush and Bryk 2002, Singer and Willett 2003, Snijders and Bosker 2012). An advantage of this approach is that it captures unobserved heterogeneity; thus, we can assess the degree of within- and between-salesperson variation.

Growth models as a type of multilevel model have long been used in the marketing literature. In the context of salesperson performance, however, growth models have only rarely been used (Ahearne et al. 2010, Fu et al. 2010). The infrequent use of growth models in this stream of literature is mostly due to the difficulty of gathering longitudinal data that fulfill the requirements for a study of change, i.e., more than three waves of data, a dependent variable that changes systematically over time, and a sensible metric measuring time (Fu et al. 2010, Singer and Willett 2003).

At level one, time-related contextual effects are indicated to predict change in salesperson performance. Thus, the influence of the time-varying variables representing a salesperson's relational and transactional selling strategies is modeled on this level. Time-varying control variables are also specified on level one. In this study, salesperson performance trajectories Y_{ij} are a function of the linear time trend.

The level-two model uses all time-invariant control variables indicating the effects of the external market environment and further characteristics specific to each salesperson. At level two, we further specify the random slopes to account for heterogeneity among salespersons. To test which level-one effects vary at level two and significantly increase the model fit, we calculate a series of log-likelihood ratio tests including random effects in a step-by-step approach (Stram and Lee 1994).[2] The model with the best fit is used as the final model.

In time-series models, the **problem of autocorrelation** arises. Specifically, as the dependent variable follows a logical order, observations of time points closer to each other may have stronger relationships than observations more distant from each other (Bliese and Ployhart 2002). Correlation structures can be used to model dependence among the within-group errors (Pinheiro and Bates 2000). To account for the autocorrelation of within-subject errors, we model a Toeplitz correlation structure of the error terms. Toeplitz errors are used when each lag (or each off-diagonal in the error variance covariance matrix) is assumed to have its own autocorrelation error (Hedeker and Gibbons 2006). Accordingly, we account for

[2] In specific, in the first step, we calculate separate models, each including one of the fixed effects as random effect. We thereby consider the hypothesized effects as well as control variables. Those models are compared to the baseline model containing only the random effect of time. In case of a significant log-likelihood ratio test between the baseline model and the model with the lowest AIC of all models calculated, the random effect from the latter model is added to the baseline model. In the next step, again, separate models are calculated each containing one of the remaining random effects. Again, the random effect significantly improving the model fit is added to the baseline model. These calculations are performed iteratively until adding a random effect no longer leads to a significant improvement of the model fit.

the correlation between the error of the current time point and the first, second, and third lag, and assume that higher-order lags have zero correlation.

The **final model has the following form**:

Level 1:

$$
\begin{aligned}
Y_{ti} = \pi_{0i} &+ \pi_{1i}\text{time}_{ti} \\
&+\pi_{2i}\text{returning customers}_{ti} + \pi_{3i}\text{returning customers}_{ti} \times \text{time}_{ti} \\
&+\pi_{4i}\text{returning customers}_{ti}^2 + \pi_{5i}\text{returning customers}_{ti}^2 \times \text{time}_{ti} \\
&+\pi_{6i}\text{price positioning}_{ti} + \pi_{7i}\text{price positioning}_{ti} \times \text{time}_{ti} \\
&+\pi_{8i}\text{product positioning}_{ti} + \pi_{9i}\text{product positioning}_{ti} \times \text{time}_{ti} \\
&+\pi_{10i}\text{timing of sale}_{ti} + \pi_{11i}\text{timing of sale}_{ti} \times \text{time}_{ti} \\
&+\pi_{12i}\text{geographic proximity}_{ti} + \pi_{13i}\text{geographic proximity}_{ti} \times \text{time}_{ti} \\
&+\pi_{14i}\text{marketing spending}_{ti} + \pi_{15i}\text{travel duration}_{ti} + \pi_{16i}\text{seasonality}_{ti} + \varepsilon_{ti}
\end{aligned}
\tag{4.2}
$$

Level 2:

$$
\begin{aligned}
\pi_{0i} = \beta_{00} &+ \beta_{01}\text{salesperson age}_i + \beta_{02}\text{salesperson gender}_i \\
&+\beta_{03}\text{number of competitors}_i + \beta_{05}\text{ZIP area}_i + u_{0i} \\
\pi_{1i} = \beta_{10} &+ u_{1i};\ \pi_{2i} = \beta_{20} + u_{2i};\ \pi_{4i} = \beta_{40} + u_{4i};\ \pi_{6i} = \beta_{60} + u_{6i};\ \pi_{7i} = \beta_{70} + u_{7i}; \\
\pi_{8i} = \beta_{80} &+ u_{8i};\ \pi_{9i} = \beta_{90} + u_{9i};\ \pi_{12i} = \beta_{120} + u_{12i};\ \pi_{15i} = \beta_{150} + u_{15i}
\end{aligned}
$$

whereby

$$\varepsilon_{ti} \sim iid\ N(0, \sigma^2_{\varepsilon_{Toeplitz}});\ u_{ki} \sim iid\ N(0, \tau_u^2);\ k \in \{0,1,2,4,6,7,8,9,12,15\}$$

We test **further necessary assumptions** underlying multilevel models by following procedures proposed by Snijders and Bosker (2012). Specifically, we test the normality assumption by inspecting the error distribution at every level of the analysis. Furthermore, we examine whether homoscedasticity exists to ensure that the errors have equal variances.

4.5 Results

4.5.1 Evaluation of the modeling approach

With our **analytical procedure**, we apply a step-by-step analysis in which we estimate an unconditional means model to evaluate the necessity of a multilevel specification, several models to assess the correct specification of time, and tests for the presence of random effects.

This procedure is consistent with the typical steps recommended for analyzing growth curve models (Singer and Willett 2003). For all models, we use the maximum likelihood estimation approach.

First, **whether estimation of a multilevel model is necessary** for our data can be evaluated by comparing the single-level unconditional means model with the two-level unconditional means model without any predictors. The log-likelihood comparison test indicates a difference in log-likelihoods of -2196.354 (df = 2). Thus, the estimation of a multilevel model is necessary. From this model, we derive the estimated values for the variation between salesperson means as well as the variation among months within the salesperson and yield an interclass correlation (ICC) of 33.73 %[3] which indicates that substantial variation in performance exists at the salesperson level.

Second, we **compare several growth models to ensure that we use the right specification of time**. Therefore, we calculate (1) a random intercept model without an effect of time, (2) a fixed linear time random intercept model, (3) a random linear time model with both random effects on the intercept and slope, and (4) a fixed quadratic random linear time model with random effects on the intercept and linear time slope.[4] Main effects and control variables are included in those models. The log-likelihood ratio tests indicate that the linear random intercept random slope model (Model (3)) has the best fit.[5] Results of this model are shown in Table 4.3. The quadratic time effect is not significant and is not considered in the final model.

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[3] The ICC is calculated as $\mathrm{ICC} = \mathrm{Var}(u_{0j}) / \left(\mathrm{Var}(u_{0j}) + e_{ij}\right) = 0.3170 / (0.3170 + 0.6229) = 33.73\ \%$.

[4] The model specifications are as follows (all models include main effects and control variables which are not shown here to simplify the formula presentation):

Model (1): Level 1: $Y_{ij} = \pi_{0j} + e_{ij}$, Level 2: $\pi_{0j} = \beta_{00} + u_{0j}$;

Model (2): Level 1: $Y_{ij} = \pi_{0j} + \pi_{1j} time_{ij} + e_{ij}$, Level 2: $\pi_{0j} = \beta_{00} + u_{0j}$;

Model (3): Level 1: $Y_{ij} = \pi_{0j} + \pi_{1j} time_{ij} + e_{ij}$, Level 2: $\pi_{0j} = \beta_{00} + u_{0j}$, $\pi_{1j} = \beta_{10} + u_{1j}$;

Model (4): Level 1: $Y_{ij} = \pi_{0j} + \pi_{1j} time_{ij} + \pi_{2j} time_{ij}^2 + e_{ij}$, Level 2: $\pi_{0j} = \beta_{00} + u_{0j}$, $\pi_{1j} = \beta_{10} + u_{1j}$.

[5] The results of the likelihood ratio tests are as follows: Model (1) and Model (2): Chisq: 270.91, df = 1, p < 0.001; Model (2) and Model (3): Chisq: 148.73, df = 1, p < 0.001; Model (3) and Model (4): Chisq: 1.64, df = 1, p > 0.1.

Table 4.3: Estimation results

	Time-only model			Linear growth curve model (excl. ref)			Linear growth curve model (incl. ref)		
	Est.	SE	Sig.	Est.	SE	Sig.	Est.	SE	Sig.
Fixed effects:									
(Intercept)	8.581	0.022	***	0.181	0.017	***	0.177	0.016	***
Time	0.114	0.012	***	0.090	0.010	***	0.082	0.010	***
Returning customers	0.375	0.018	***	0.372	0.016	***	0.355	0.017	***
Returning customer × time				0.092	0.015	***	0.095	0.015	***
Returning customers^2	-0.405	0.018	***	-0.393	0.016	***	-0.382	0.017	***
Returning customers^2 × time				-0.038	0.015	*	-0.041	0.015	**
Price positioning	-0.066	0.006	***	-0.045	0.005	***	-0.020	0.007	**
Price positioning × time				0.031	0.005	***	0.022	0.006	***
Product positioning	-0.099	0.006	***	-0.082	0.005	***	-0.092	0.007	***
Product positioning × time				-0.018	0.005	***	-0.012	0.006	*
Timing of sale	0.148	0.007	***	0.118	0.006	***	0.114	0.006	***
Timing of sale × time				0.008	0.005	.	0.009	0.004	*
Geographic proximity	-0.056	0.008	***	-0.046	0.007	***	-0.058	0.008	***
Geographic proximity × time				-0.002	0.005	ns	0.001	0.006	ns
Control variables:									
# competitors	-0.016	0.024	ns	-0.014	0.020	ns	0.001	0.015	ns
Marketing spending	0.023	0.007	***	0.019	0.006	***	0.017	0.005	**
Travel duration	0.232	0.007	***	0.188	0.006	***	0.222	0.008	***
Age	0.047	0.019	*	0.041	0.015	**	0.027	0.012	*
Gender	0.035	0.018	.	0.030	0.014	*	0.008	0.011	ns
ZIP code area	[a]			[a]			[a]		
Seasonality	[a]			[a]			[a]		
Random effects:	Est.	STD		Est.	STD		Est.	STD	
Intercept (ID)	0.264	0.514		0.170	0.411		0.129	0.359	
Time	0.021	0.146		0.013	0.116		0.014	0.120	
Returning customers							0.018	0.135	
Returning customers^2							0.020	0.142	
Price positioning							0.006	0.075	
Price positioning × time							0.003	0.056	
Product positioning							0.014	0.117	
Product positioning × time							0.003	0.054	
Geographic proximity							0.008	0.087	
Travel duration							0.012	0.111	
Residual	0.473	0.688		0.306	0.553		0.272	0.522	
Model fit:									
AIC		35312.5			28371.8			27709.4	
BIC		35596.6			28702.1			28439.0	
Log Likelihood		-17619.2			-14142.9			-13759.7	
Deviance		35238.5			28285.8			27519.4	

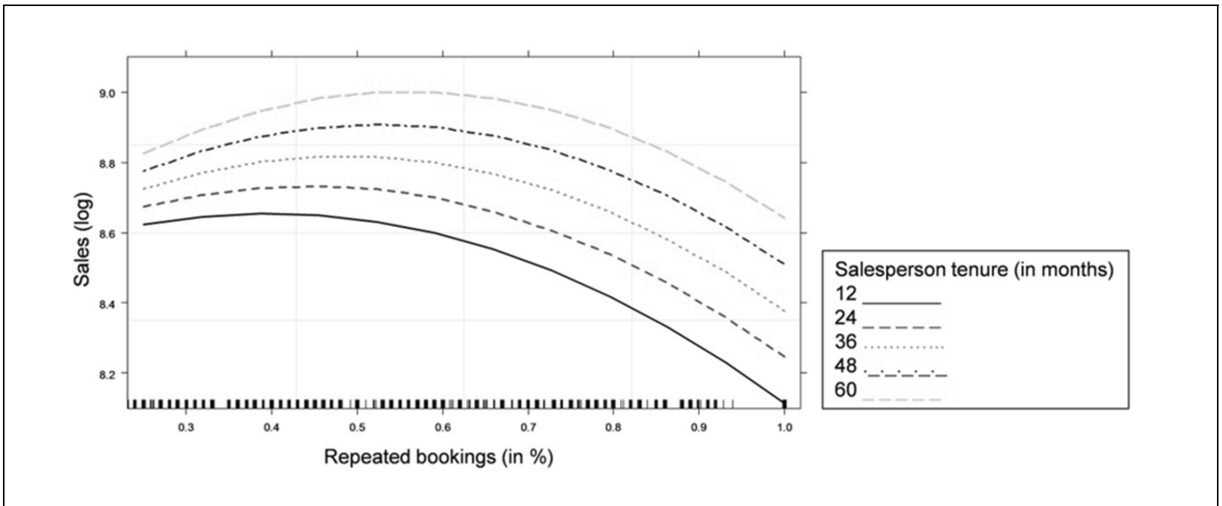
Note: *** = 0.001, ** = 0.01, * = 0.05, **.** = .1; number of observations: 15985, number of groups: 812; [a] Effects are measured by several binary variables which are not shown to simplify the presentation (ZIP code area is measured by nine and seasonality by eleven binary variables); Est. = standardized estimates, SE = standard error, STD = standard deviation, Sig. = significance, ns = not significant, ref = random effects.

Third, for our **final conditional linear growth model**, we add the interaction effects with time and the random effects as indicated in Formula 4.2. The estimation results for the final model are presented in Table 4.3.

4.5.2 Relational selling strategy

Regarding the **effect of a salesperson's relational selling strategy** on salesperson performance, we hypothesized an inverted U-shaped relationship (H1a) that depends on the salesperson's tenure (H1b). Examining the effects presented in Table 4.3, we find support for both hypotheses. The results show a significant U-shaped relationship (positive linear effect ($b = 0.355$, $p < 0.001$) and negative quadratic effect ($b = -0.382$, $p < 0.001$) of returning customers), and significant interactions with the effect of time, i.e., the salesperson's tenure in the market ($b = 0.095$, $p < 0.001$; $b = -0.041$, $p < 0.01$). These results indicate that the number of returning customers increase with the salesperson's tenure and, in turn, positively influence salesperson performance. This relationship is quadratic; hence, an optimal number of returning customers exists which increases over time.

Figure 4.4: The dynamic effect of relational selling strategy on performance

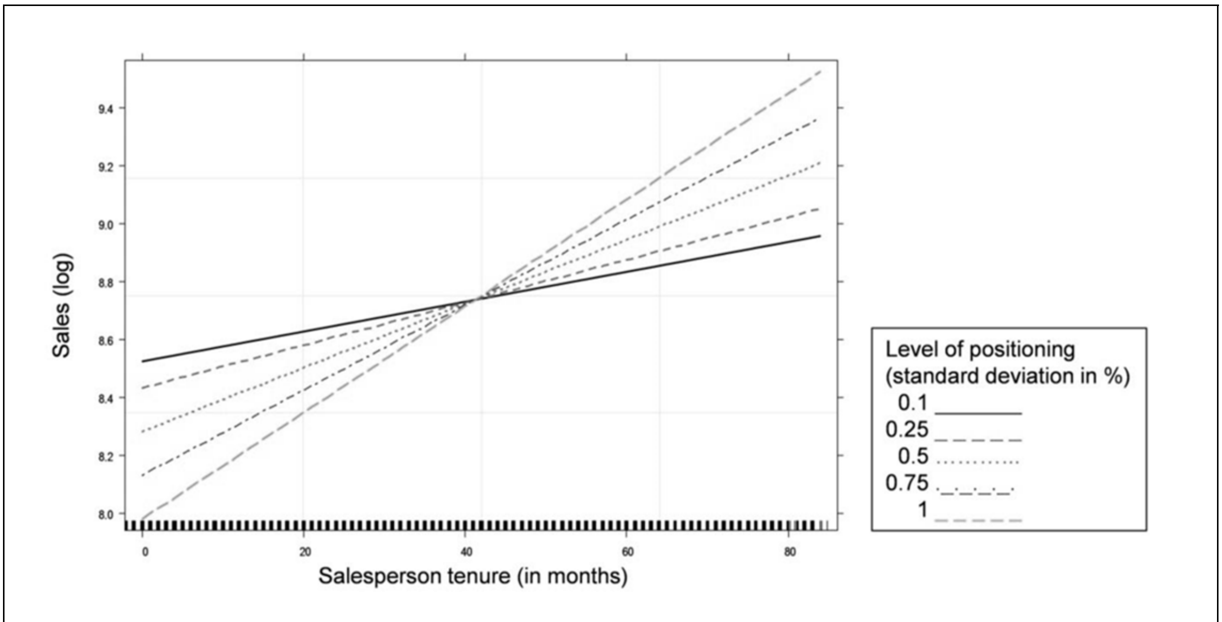


The **interaction effect is visualized** in Figure 4.4. The quadratic effect of returning customers is indicated for salespersons with varying months of tenure. In general, the number of returning customers is greater for salespersons with more time operating in the market. Because of the quadratic relationship, the curves show an increase and a shift to the right of the optimum with increasing tenure.

4.5.3 Transactional selling strategy

In our model, the influence of a salesperson's transactional selling strategy on the salesperson's performance is represented by several factors. First, we hypothesized a positive effect of **price positioning** on salesperson performance (H2a) which increases with the salesperson's tenure (H2b). Examining the result in Table 4.3, we find partly support for both hypotheses. Until a certain point in time, specializing on a specific price segment enhances salesperson performance (see Figure 4.5). However, after this point, this relationship reverses; thus, for salespersons with a longer tenure, offering products from a broader price range becomes more important (the negative effect of price positioning ($b = -0.020$, $p < 0.01$) is weakened through the positive interaction effect with time ($b = 0.022$, $p < 0.001$)).

Figure 4.5: The dynamic effect of price positioning on performance



Second, a positive effect of **product positioning** on salesperson performance was hypothesized (H3a) which increases with the salespersons' tenure (H3b). We find that product specialization increases salesperson performance and that its importance increases with time (the negative effect of product positioning ($b = -0.092$, $p < 0.001$) is reinforced by the negative interaction with time ($b = -0.012$, $b < 0.05$)). These results support both hypotheses.

Third, we hypothesized a positive effect of **selling products in advance on salesperson performance** (H4a) which increases with the salesperson's tenure (H4b). The results support the existence of a positive relationship ($b = 0.114$, $p < 0.001$), indicating that selling more in advance increase salesperson performance. Results also indicate a dynamic effect of this relationship ($b = 0.009$, $p < 0.05$). Thus, both hypotheses can be accepted.

Finally, we hypothesized that closer **geographic proximity** has a positive influence on salesperson performance (H5a) which decreases over time (H5b). We find support for H5a. The significant negative effect ($b = -0.058$, $p < 0.001$) indicates that a closer proximity between the salesperson and the customer enhances performance. However, there is no significant interaction between geographic proximity and time ($b = 0.001$, $p > 0.1$). Thus, H5b must be rejected.

4.5.4 Effects of the control variables

We include several control variables in the model. Regarding the **macro-environmental characteristics**, we find no significant effect for the number of competitors ($b = 0.001$, $p > 0.1$). Further, we included several binary variables to control for ZIP code area and seasonality.

Regarding **salesperson characteristics**, we find a positive effect of marketing spending on performance ($b = 0.017$, $p < 0.01$), indicating that investment in promotional material could enhance a salesperson's performance. The effect of travel duration is positive and significant ($b = 0.222$, $p < 0.001$), indicating that increased travel duration of customers has a greater effect on performance. The effect of age is positive and significant ($b = 0.027$, $p < 0.05$), thus, performance increases with the salesperson's age. The effect of gender is not significant ($b = 0.008$, $p > 0.1$).

4.6 Discussion

4.6.1 Implications

This study aimed to analyze the dynamic effects of relational and transactional selling strategies on salespersons' performance. We complement previous studies by accounting for the dynamic nature of both salesperson performance and its drivers. Applying a linear growth curve model, we analyze monthly sales data for 812 independent salespersons from the tourism industry over a period of eight and a half years and find broad support for our hypotheses.

This study has several **important managerial implications**. In general, analyzing salesperson performance over time allows a more precise and reliable identification of relevant determinants. By considering the dynamic influence of relational and transactional selling strategies, this study offers managers a tool for (1) evaluating current salesperson performance and (2) forecasting future salesperson performance by accounting for various contextual effects.

First, continuously **evaluating the current salesperson performance** is one of sales managers' core tasks. The challenge for such an evaluation is to overcome the common practice of focusing on short-term changes and neglecting long-term changes in the development of salespersons performance. In addition to establishing more accurate benchmarks for static evaluations of salesperson performance, our study illustrates how managers can evaluate salespersons in terms of (1) their general tendency to underperform or outperform others over time and (2) their individual strengths and weaknesses in relation to relevant drivers of salesperson performance. Managers adopting this approach can make more informed decisions in developing a firm's salesforce by identifying salespersons who meet a certain set of criteria, e.g., those who consistently outperform others.

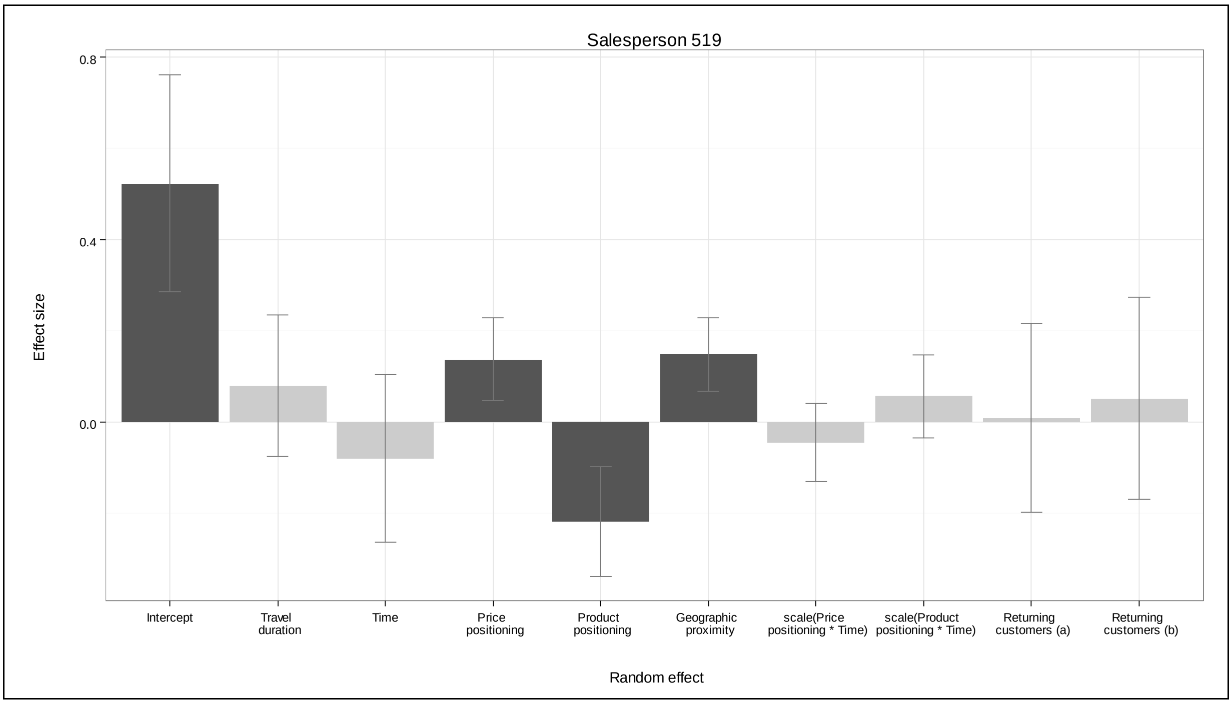
Specifically, by modeling the general growth pattern of salesperson performance as random effects, we are able to **assess how a salesperson's individual growth trajectory devi-**

ates from the average growth trajectory. By comparing the two parameter estimates for the linear time effect, i.e., the fixed effect and the individual-level Empirical Bayes estimate of the random effect, managers can assess whether a salesperson underperforms or outperforms. For example, this approach could be used to reward salespersons by identifying salespersons with superior performance. Furthermore, this approach could be used to identify underperforming salespersons. Sales managers should then determine the underlying reasons for such underperformance and support these salespersons to enhance their performance, e.g., by an individual coaching.

Additionally, sales managers should **evaluate the efficiency of salespersons with respect to the relevant drivers** of salesperson performance. In this way, the sales manager can develop a more detailed understanding of a salesperson's strengths and weaknesses. By identifying the salespersons who struggle in certain areas, sales managers can offer customized trainings to address salespersons' weaknesses. For example, salespersons who are not focusing on relationship building could receive trainings on developing and enhancing skills which help to build better and long lasting bonds with customers.

Figure 4.6 shows an **example evaluation of the individual performance** of a randomly chosen salesperson. By calculating the Empirical Bayes estimates of the random effects, the salesperson's individual deviation from the fixed effects is determined. For the salesperson in the example, no significant individual deviation exists in terms of the growth parameter (i.e., time) and the salesperson's relational selling strategy.

Figure 4.6: Example evaluation of individual salesperson performance



Note: Grey bars indicate performance drivers where no individual deviation exists; black bars indicate performance drivers with individual differences; returning customers (a) refers to the linear effect of this variable; returning customers (b) refers to the quadratic effect of this variable.

However, **individual differences occur** in terms of the salesperson's base sales (i.e., intercept) and elements of the transactional selling strategy. This salesperson shows much higher base sales compared to other salespersons. Concerning price positioning and geographic proximity, the negative effects are decreased indicating that strong price positioning and a close proximity to the customer is less important for this salesperson's performance compared to other salespersons. Regarding product positioning, the negative effect is enhanced indicating that a strong product positioning is more important for the performance of this salesperson than for that of other salespersons.

A second major implication of our study concerns **assessments of future salesperson performance.** Sales forecasting plays a key role for businesses. Sales managers' decisions concerning future actions rely heavily on the information provided by sales forecasting. A suitable forecasting system is necessary to plan inventory, determine how to serve customers better, and increase profit and anticipated future growth. Simulation studies have shown that a multilevel approach outperforms traditional approaches, such as ordinary least squares, in prediction (Afshartous and Leeuw 2005, Hofmann 1997). Our model can easily be adapted to provide context specific predictions of salespersons' future sales and, thus, enables sales managers to delegate salespersons more efficiently, i.e., by setting realistic sales targets on an individual level basis.

4.6.2 Limitations and further research

Certain **limitations of our study** provide an agenda for future research. Worthwhile research paths would be to enrich our analysis by (1) enhancing the breadth of the data basis, i.e., the observations, and by (2) enhancing the depth of the data basis, i.e., the variables.

First, our analysis could be enhanced by **increasing the breadth of the data**, for instance by including data from other firms in the same industry. In addition, future research should consider data from other industries, for example, the insurance industry. Data from both other firms and other industries would enhance the generalizability of our results. Furthermore, our model could be adapted to the context of non-independent salespersons.

Second, future research could **enhance the depth of the data**, i.e., include additional variables in the model. An interesting avenue would be to consider more product details. Using data from the tourism industry, a study could include details on travel destinations or travel purposes (e.g., business, leisure, or study-related travelling; this study analyzes data on leisure travel only). Additionally, including information on salesperson's consultancy efforts, e.g., the time from the initial contact to the customer's purchase of the product, would offer further insights into a salesperson's efficiency and productivity. Furthermore, regarding the salesperson's effort in relationships with customers, variables on a salesperson's investment in acquiring new versus retaining existing customers could provide guidance on how to optimally allocate promotional budgets (Berger and Nasr 1998). Moreover, ideally, the analysis would be enhanced by including survey data on salespersons (e.g., attitudes, motivation, and organizational identification) and customers (e.g., buying intentions, satisfaction with the salesperson). However, addressing performance dynamics – and thus using a repeated-measures design for the survey – would require substantial time.

In summary, our research sheds light on relational and transactional selling strategies as drivers of salesperson performance and highlights the importance of modeling their dynamic effects. At the same time, we illustrate how to individually assess salesperson performance and the impact of its drivers. We recommend that sales managers assessing the performance of their salesforce avoid focusing on factors that salespersons cannot control, understand the difference between superior performance based on luck and superior performance based on skills, and to focus on persistent and predictive metrics that measure salespersons' actual behavior. Through such an assessment, sales managers can enhance the success of their salespersons and firm.

Appendix

Appendix 4.1: Cross-sectional salesperson performance studies

META STUDIES

Studies	Determinants of salesperson performance
Churchill et al. (1985)	Personal factors, skills, role variables, aptitude, motivation, organization-al/environmental factors
Franke and Park (2006)	Adaptive selling behavior, customer orientation, job satisfaction
Verbeke et al. (2011)	Strongest determinants: selling-related knowledge, degree of adaptiveness, role ambiguity, cognitive aptitude, work engagement
Vinchur et al. (1998)	Biodata measures (e.g., achievement, general cognitive ability, openness, age, etc.)
Zablah et al. (2012)	Customer orientation (moderation through role conflict/ambiguity, satisfac-tion, organizational commitment)

SUBJECTIVE PERFORMANCE MEASURES

Studies	Determinants of salesperson performance
Measure of salesperson performance: supervisor rating	
Babakus et al. (1996)	Sales management control system, organizational design, behavioral per-formance
Barrick et al. (2002)	Extraversion, conscientiousness, status and accomplishment striving
Brown and Peterson (1994)	Role ambiguity, role conflict, competitiveness, instrumentality
Cron and Slocum (1986)	Career stage, business strategy, job attitudes, work perceptions, age
Korschun et al. (2014)	Organizational identification, employee-customer identification, perceived management corporate social responsibility (CSR), perceived customer CSR
MacKenzie et al. (1993)	Organizational citizenship behavior, objective sales productivity
MacKenzie et al. (1998)	Role conflict/ambiguity, in-role performance, job satisfaction, organizational commitment
Menguc et al. (2013)	Task independence, empowering leadership, customer knowledge creation capability
Steward et al. (2010)	Internal relationships (reputation, diversity, tie strength), coordination of ex-perience
Venkatesh et al. (2001)	Career stage, competence, rewards, learning orientation
Yim et al. (2012)	Customer participation, self-efficacy, other-efficacy, employee participation enjoyment, job satisfaction
Measure of salesperson performance: self-rating	
Atuahene-Gima and Li (2002)	Supervisors behavior, sales controls, supervisee trust
Babakus et al. (1999)	Emotional exhaustion
Boorom et al. (1998)	Indirect: communication apprehension, mediation through interaction in-volvement, adaptiveness
Challagalla and Shervani (1996)	Output control, activity control, capability control
De Ruyter et al. (2001)	Empowerment autonomy, empowerment competence, leader consideration, role ambiguity, role conflict, job satisfaction
Evans et al. (2007)	Output controls
Grant et al. (2001)	Satisfaction with territory design, role ambiguity, intrinsic motivation
Homburg et al. (2011b)	Customer orientation
Jaworski and Kohli (1991)	Positive/negative output/behavioral feedback, role clarity
Kohli and Jaworski (1994)	Conformity, experience, self-feedback, neg./pos. output/behavioral coworker feedback
MacKenzie et al. (2001)	Transformational, transactional leadership (incl. company records)
Miao and Evans (2013)	Outcome, activity, and capability control, job engagement, job stress

Appendix 4.1 (continued)

Ramaswami and Singh (2003)	Performance improvement plan, linkage to rewards, application of performance standards, performance measure appropriateness, mediated through performance improvement plan, supervisor trust
Román and Iacobucci (2010)	Adaptive selling behavior, replication hypothesis of intrinsic motivation, customer-qualification skills
Shannahan et al. (2013)	Transformational leadership, trait competitiveness, coachability
Singh (1998)	Role conflict/ambiguity, task variety, autonomy
Singh (2000)	Supervisor support, task control, role stressors, burnout tendencies
Swenson and Herche (1994)	Achievement (self-fulfillment, self-respect, sense of accomplishment, being well-respected), social value (sense of belonging, relationships with others)
Wieseke et al. (2009)	Organizational identification (employee and manager)
Measure of salesperson performance: supervisor-rating and self-rating	
Brown et al. (2002)	Introversion, instability, agreeability, conscientiousness, activity, customer orientation
Plouffe et al. (2009)	Sales orientation/ customer orientation, adaptive selling, sales service behaviors, selling skills
Rich (1997)	Trust in sales manager, mediation through role modeling

OBJECTIVE PERFORMANCE MEASURES

Studies	Performance measure	Determinants of salesperson performance
Ahearne et al. (1999)	Market share	Attractiveness, length of buyer-salesperson relationship, perceived communication ability, likeability, trustworthiness
Ahearne et al. (2007)	Total year bonus/commission per salesperson based on achieved sales levels	IT acceptance, mediated through call productivity, targeting skills, sales presentations
Ahearne et al. (2013a)	Percentage attainment of sales quotas	Organizational identification, interpersonal identification congruence, perceived managerial control system
Ahearne et al. (2013b)	Sales quota achievement	Competitive intelligence, customer orientation, sales experience, product knowledge, job satisfaction, network centrality
Brown et al. (1998)	Number of products sold in 90-days promotion period	Self-set goal level, self-efficacy
Homburg et al. (2011c)	Annual sales volume	Corporate management effects, leadership, support, negative stereotypes
Hughes and Ahearne (2010)	Brand sales performance	Brand identification, brand effort, brand extra-role behavior
Hughes (2013)	Percentage attainment of sales quotas	Perceived ad quality and quantity, brand identification, outcome expectancy, effort
Jasmand et al. (2012)	Weekly average call handling time, conversion rate, customer satisfaction	Ambidexterity
Kidwell et al. (2011)	Annual sales volume	Emotional intelligence, cognitive ability
Gonzalez et al. (2014)	Annual sales growth	Commitment velocity, commitment level, governing, exploring and exploiting mechanisms
Rapp et al. (2006)	Market share of prescriptions for the branded product represented by the salesperson	Experience, knowledge, leader behavior, working hard/smart, customer service and satisfaction
Verbeke et al. (2008)	Net sales volume in year preceding the study	General mental ability, social competence, judicial style, specific skills
Wotruba (1990)	Earnings per hour (based on two questionnaire answers)	Part-time vs. full-time workers

Note: This overview covers articles published between 1990 and 2013 in the Journal of Marketing, the Journal of Marketing Research, the International Journal of Research in Marketing and the Journal of the Academy of Marketing Science. While determinants can have indirect or direct effects and can be moderators or mediators, these distinctions are not relevant for this study.

Appendix 4.2: Correlation matrix

	SAL	T	REL	PRI	PRO	TIM	GEO	DUR	COM	MKT	AGE	GEN
SAL	1											
T	0.17	1										
REL	0.07	0.46	1									
PRI	-0.10	-0.07	0.01	1								
PRO	-0.20	-0.01	-0.02	0.08	1							
TIM	0.22	0.00	0.02	0.00	-0.09	1						
GEO	-0.09	-0.06	-0.03	0.01	-0.02	-0.02	1					
DUR	0.22	-0.01	-0.05	0.06	0.03	0.21	0.00	1				
COM	-0.08	-0.04	0.03	0.04	0.03	-0.02	0.06	0.05	1			
MKT	0.14	0.03	-0.02	-0.01	-0.04	0.00	-0.05	-0.02	-0.07	1		
AGE	0.09	0.15	0.10	0.01	-0.04	0.03	-0.03	0.10	0.12	0.04	1	
GEN	0.03	0.07	0.04	0.01	0.02	0.04	-0.03	-0.01	-0.09	0.01	-0.08	1

Note: SAL = sales, T = time, REL = returning customers, PRI = price positioning, PRO = product positioning, TIM = timing of sale, GEO = geographic proximity, DUR = travel duration, COM = number of competitors, MKT = marketing spending, AGE = age, GEN = gender. Factor variables for seasonality and ZIP code area are not shown to simplify the presentation of the correlations.

Appendix 4.3: Basic descriptive statistics

Time [a]	No. of transac-tions mean	Minimum no. of transac-tions	Maximum no. of transac-tions	STD of no. of transac-tions	No. of sales-persons	Mean sales (in €)	Minimum sales (in €)	Maximum sales (in €)	STD of sales (in €)
1	3.41	2	16	2.06	485 [b]	5905.75	46.00	38133.52	5244.90
2	4.37	2	40	3.56	452	7475.74	200.00	84896.28	8472.37
3	4.78	2	41	3.96	432	8128.83	113.00	97143.53	9299.96
4	4.82	2	25	3.66	433	8385.58	265.00	84232.93	8539.77
5	4.58	2	27	3.24	426	8574.49	221.00	140595.60	10580.96
6	4.91	2	28	3.43	373	8576.40	255.50	68617.00	8326.94
7	4.66	2	24	3.63	406	7801.64	204.00	52202.00	7797.59
8	4.74	2	29	3.30	383	8236.05	251.00	56211.40	7878.40
9	4.89	2	31	3.60	396	8499.39	250.00	81366.00	9038.87
10	4.85	2	32	3.75	373	8465.47	173.00	69602.04	8200.74
11	5.01	2	33	3.96	362	7983.41	206.00	61456.17	7880.01
12	5.05	2	28	3.72	333	9160.37	466.00	53727.86	8426.14
13	4.97	2	20	3.35	350	8896.61	182.00	56377.60	8204.50
14	5.14	2	33	3.90	354	9272.84	242.00	50856.28	8953.52
15	5.42	2	32	3.71	340	9940.55	367.10	58146.97	9260.85
16	5.71	2	37	4.53	330	9964.24	208.00	94562.43	10068.17
17	5.06	2	23	3.74	308	9110.68	191.89	89856.39	9300.38
18	5.18	2	21	3.62	322	9708.61	230.00	75406.90	10392.08
19	5.14	2	23	3.88	310	8180.52	126.00	61365.00	8100.02
20	4.82	2	26	3.40	316	8477.60	97.00	37600.00	6753.27
21	5.32	2	22	3.81	291	9257.58	204.98	52359.10	8114.20
22	5.40	2	39	4.39	284	9675.24	37.00	54192.15	8735.48
23	5.52	2	37	4.69	284	10040.42	315.69	55545.63	9745.18
24	5.51	2	26	3.86	278	9947.24	140.00	57321.00	9054.69
25	5.20	2	24	3.59	291	10168.26	124.30	67554.25	9639.28
26	5.23	2	34	3.78	285	10162.44	480.00	66822.28	9263.02
27	5.71	2	25	4.41	250	10446.04	275.81	74414.00	9932.18
28	5.72	2	31	4.42	261	9920.28	452.00	58412.34	9105.32
29	5.49	2	36	4.47	255	9987.66	116.00	46073.66	8834.87
30	5.53	2	25	3.89	234	9965.61	460.00	65870.79	8791.81
31	5.39	2	22	3.87	236	9845.71	436.00	56786.91	8691.13
32	5.22	2	32	4.16	244	9561.82	218.00	44240.79	7645.39
33	5.51	2	26	3.77	230	10712.13	315.07	54444.15	9424.86
34	5.64	2	36	4.57	227	10339.72	286.00	49653.32	9208.06
35	5.69	2	32	4.55	216	10696.50	81.00	62905.20	9871.56
36	5.49	2	26	4.37	198	10266.64	166.00	67712.60	10007.54
37	5.46	2	24	4.07	178	9890.94	460.95	75983.43	9488.27
38	5.12	2	20	3.52	185	8949.97	266.00	62361.00	8192.12
39	5.67	2	23	4.30	165	10759.48	60.00	78726.73	12089.57
40	5.80	2	37	4.81	177	11291.37	416.00	108385.21	12252.90
41	5.46	2	25	4.17	164	10305.75	606.00	52214.88	8924.51
42	5.74	2	34	4.73	152	10394.86	142.00	109851.39	12086.05
43	5.75	2	31	4.45	157	10408.87	616.00	47550.26	8766.34
44	5.75	2	31	4.32	138	10391.74	498.00	77197.80	9635.32
45	5.62	2	26	4.52	141	10430.27	241.00	61716.05	10112.90
46	5.57	2	50	5.17	138	11202.36	328.00	85394.11	11100.23
47	5.43	2	31	4.18	138	10315.32	633.60	60076.60	9347.12
48	6.17	2	28	4.66	123	11503.78	532.00	53741.07	9344.76
49	6.00	2	29	4.70	117	11974.72	375.20	39200.47	9528.09
50	5.88	2	24	4.05	121	11810.23	506.00	46117.80	10097.62
51	6.16	2	23	4.23	116	11765.56	528.75	44585.23	10168.71
52	5.86	2	38	5.68	118	10903.57	304.00	59279.62	11079.96
53	5.79	2	24	4.38	110	11870.48	699.00	63705.31	11148.93
54	5.34	2	26	4.08	105	10382.33	1588.80	42445.26	8237.55
55	6.41	2	26	4.88	97	11577.57	478.00	43809.29	9171.86
56	5.79	2	23	4.03	91	11801.52	588.00	56088.18	9878.97

Appendix 4.3 (continued)

57	5.21	2	20	3.65	91	9873.11	397.99	43695.06	8855.94
58	6.65	2	63	7.39	88	12311.31	544.00	116083.47	14727.98
59	5.04	2	22	3.79	90	9840.32	445.00	38111.99	8424.48
60	6.00	2	28	4.75	85	13964.68	488.00	102821.74	13948.33
61	6.15	2	24	4.81	74	13496.10	1443.00	60737.00	12594.74
62	5.89	2	17	3.76	70	11688.79	184.00	35124.66	8538.11
63	6.74	2	25	5.06	68	12648.46	736.73	50982.00	10763.27
64	6.62	2	30	4.78	74	12832.42	244.00	56701.45	10395.27
65	5.90	2	30	4.81	73	11213.42	614.00	38460.39	8503.64
66	5.99	2	14	3.57	67	11698.98	614.00	47292.00	9863.88
67	5.34	2	20	3.34	65	10629.32	807.00	69384.01	9710.31
68	5.98	2	17	3.64	59	12622.18	906.00	41422.00	10047.65
69	5.33	2	17	3.12	63	10046.82	475.95	31752.50	7010.38
70	6.19	2	21	3.93	52	13956.59	2190.00	55636.88	10475.01
71	4.73	2	14	3.12	51	9405.25	736.92	27102.80	7175.63
72	5.24	2	17	3.55	49	11564.76	144.00	39451.63	9588.37
73	5.57	2	19	3.51	46	12039.89	855.42	50857.30	11400.23
74	5.21	2	16	3.34	47	10647.47	1386.00	40441.07	8243.50
75	6.35	2	24	4.96	37	13028.54	1882.00	44637.23	10136.88
76	6.89	2	20	4.62	36	14203.35	1906.00	40897.00	9551.07
77	6.47	2	17	4.23	36	14195.45	916.44	34644.70	10074.20
78	5.53	2	19	3.55	34	11754.85	499.00	38815.60	9240.95
79	5.47	2	19	3.45	32	13956.97	1326.00	54888.63	11775.36
80	5.74	2	17	3.58	35	11693.30	1852.09	41718.00	8324.67
81	5.82	2	17	3.40	33	12335.17	2281.45	37405.31	8136.86
82	6.24	2	28	5.40	34	13068.24	1339.66	48929.44	12368.63
83	6.24	2	14	3.81	25	12923.20	1717.00	32092.21	9944.50
84	7.00	3	22	5.33	21	13936.03	454.00	44506.00	11892.46
85	4.58	2	12	2.84	24	9942.95	580.95	24304.43	6901.71
86	7.12	2	12	3.26	17	15672.75	1620.00	31274.84	8979.94
87	7.05	2	22	5.47	20	15534.84	1996.40	62217.60	16248.81
88	6.17	2	14	3.00	18	14285.29	3836.06	30493.90	8075.76
89	6.88	2	14	4.01	16	13382.22	1974.00	31936.50	9930.93
90	5.61	2	12	3.42	18	10577.53	1380.00	30633.44	9237.58
91	6.36	2	13	3.65	14	12406.10	1287.00	42782.60	11346.42
92	6.92	2	16	3.68	12	13230.59	1856.00	28383.10	8292.11
93	5.55	2	13	4.25	11	12967.06	1149.30	35513.00	11022.83
94	6.44	3	18	4.75	9	11274.31	3136.00	39714.62	11705.39
95	3.38	2	8	2.00	8	10811.76	1863.02	29719.48	9514.58
96	4.50	4	5	0.71	2	7705.48	6820.96	8590.00	1250.90
97	4.50	4	5	0.71	2	10581.30	3234.35	17928.25	10390.16
98	2.00	2	2	NA	1	2864.00	2864.00	2864.00	NA

Note: [a] The dataset covers 102 months (April 2005 until September 2013); the longest salesperson tenure is 98 months; [b] The number of salespersons in t =1 does not add up to 812 because of two reasons: (1) Some salespersons do not make any transactions in their first months of operation; (2) for salespersons who only make one transaction in a month, standard deviations for some variables in the model cannot be calculated; thus, this month is excluded from the analysis; STD = standard deviation.

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